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“Real stupidity beats artificial intelligence every time.”

Terry Pratchett in *Hogfather*
RIJKSUNIVERSITEIT GRONINGEN

Faculty of Mathematics and Natural Sciences

Abstract

Agent-based consumer modelling of the Dutch lighting market

by G.H. Schoenmacker

This document is a master’s thesis implementing a multi-agent consumer modelling system for the Dutch lighting market based on the Consumat II psychological model of consumers by Jager and Janssen [1]. The two main questions are (I) how can we implement such a model and (II) how can we facilitate adoption of energy-efficient technologies in the lighting market?

The design and implementation of the multi-agent system will be discussed and several experiments will be run with different variants of the model, showing (1) a homo economicus perspective, (2) a model using only functional behavioural strategies and (3) the full model employing functional and social strategies. A reference study containing relevant market research [2] will be used to provide data for parametrisation and comparison.

The developed model proves complex enough to exhibit behaviour as seen in the reference study [2] and provides validation for the conclusions drawn. The most important findings of this thesis are:

- Habitual behaviour is the most prominent reason for lack of adoption of energy-efficient technologies in the lighting market.

- Social behaviour helps facilitate diffusion of new technologies in the lighting market.

- The developed model replicates behaviour as observed in the reference study [2] and can confirm its conclusions.
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Chapter 1

Introduction and research questions

1.1 Introduction

In this thesis, I will focus on the implementation of a functional model of consumer behaviour to answer the question how to introduce energy-efficient lighting and light bulbs in such a way that it will be adopted by consumers. To achieve this, I will create a multi-agent computer model based on the Consumat model [3] and use data from two master’s theses [4] [2] on consumer modelling and consumer choices in the area of lighting. In the following section, I will introduce the field of consumer modelling in general and the topic of this study, lighting and light bulbs, in particular. After this, I will expand on multi-agent modelling and the Consumat model to be used. Lastly I will use this information to formulate the research questions to be answered in this study.

1.1.1 Consumer modelling

In the field of economics, especially in the area of marketing research, the behaviour of consumers is an important aspect in decision-making and models. To study consumer behaviour is to study the psychology of the individual as well as group behaviour, the social aspects of human dynamics and how these are combined in decision-making processes in different cultures. The behaviour of consumers is of obvious interest to businesses trying to promote and sell their products. Possible questions a company might ask are (i) to whom should we advertise our product for most effective exposure; (ii) which price scheme will maximise our profits; or (iii) how can we best introduce a new product. Having a model of how and why consumers behave the way they do is
paramount to answering these questions. Thus, the study of consumer behaviour is vital to groups who want to influence the choices consumers make.

An important aspect of the lighting market in particular is the fashion aspect of home decoration. As with any fashion, social considerations can dictate what consumers choose to purchase, for example by enticing people to invest in expensive technology as a means to gain social favour. This is an aspect I hope to capture in the model. Understanding of this phenomenon can also ease the passage to a more sustainable society.

Among those groups wanting to influence consumer behaviour are governments. In the European Union we have recently seen a powerful example of this in the area of lighting, when a collective ban was agreed on energy inefficient incandescent light bulbs, which were phased out over a period of three years; the ban was in full effect in 2012 [2]. Obviously, a ban on a certain product will change consumer behaviour by effectively reducing the choices a consumer has. However, the field of light bulbs remains heterogeneous with a plethora of options regarding (among others) brightness, colour, dispersion, dimming, energy efficiency, fixture-fittings and retail price. Traditionally, energy-efficient lighting has had start-up difficulties, negative colour considerations as well as problems with its image. In this study, I aim to create a multi-agent model of this market and its consumers to facilitate consumer adoption of energy-efficient technologies.

When introducing new products, the success or failure often hinges on social influences. Because of our social complexity and the many interactions we have, predicting these social effects - and thus the success of a new product - is exceedingly difficult. A better understanding of the mechanisms involved can aid the development of more effective marketing strategies.

1.1.2 Multi-agent models

Agent-based modelling is a powerful tool to formalise and visualise dynamic systems in which autonomous agents operate. It consists of a computer simulation, which is given characteristics of the agents themselves and the environment. In this simulation, each agent attempts to fulfil its given policy to the best of its capabilities. From each individual’s behaviour emerges a dynamic which can be used to predict the outcome of different scenarios. The allure of multi-agent simulation as a research tool lies in the ease with which parameters can be altered to both the agents as well as the environment, combined with the speed at which simulations can be run. Examples of published research using this method in related fields can be found in the sources [5][6][7].
The Consumat model for consumer modelling was introduced by W. Jager in his PhD thesis [3] and later expanded to create the Consumat II model by W. Jager and M. Jansen [1]. The Consumat is an abstraction of a consumer, which has needs and aims toward fulfilling these needs by taking one of four actions: (1) repetition; (2) imitation; (3) enquiring; and (4) optimising. The first means simply to ignore other options and to select the same action as before. Imitation is the act of looking at peers - individuals which closely resemble it - and selecting one of their actions. Enquiry is to consider the actions of all other agents as a next option. Lastly, optimisation means to consider the merits of all possible options and make an informed decision based on this.

Each time an action is needed, the Consumat decides on one of these actions based on its existential, social and personal needs, tolerance for uncertainty, and previous satisfaction. In general, if the agent is satisfied, it will not deviate far from its previous choices, selecting either repetition or imitation. Likewise, if the agent is uncertain about its future, it will more likely choose either imitation or enquiry because of the social connotations.

Characteristics of consumers can thus be related to their behaviours. If an agent highly regards functionality, it will try to optimise for its own existence needs whereas a most socially (or likewise: anti-socially) minded agent will more likely look to its peers for options to either fit in or stand out. Clearly people have different reasons and priorities for making purchases and using the Consumat II model; I hope to capture this.

Using this model, a simulation can be made of the lighting market and its consumers.

1.2 Research questions

1.2.1 Implementation-specific research questions

As stated before, the goal of this thesis is the implementation of a multi-agent model to facilitate an analysis of the lighting market by applying the Consumat model and using data from previous studies. The main research question will therefore be:

(I) How can we implement a multi-agent system to aid the analysis of the lighting market based on the Consumat II model?

From this main research question, several interesting questions follow:

(I.a) How can we best represent our domain-specific knowledge for efficient use by the model?
(I.b) How can we best formalise the behaviour of the model for computational efficiency?

(I.c) How can we best identify which consumer characteristics are sufficient and suited to model our chosen field?

(I.d) How can we best model social influence for the agents in the Consumat II model for our model?

(I.e) Is Consumat II sufficient to model the lighting market and consumers as found in a previous market analysis [2]?

(I.f) How can we improve the Consumat II model for future research?

1.2.2 Domain-specific research questions

Because the technique of multi-agent modelling is not a goal in itself, the domain-specific questions to be answered are a good indication of whether I have succeeded in modelling the domain. The main domain related question is:

(II) How can we facilitate adoption of energy-efficient technologies in the lighting market?

Related to this question, the following questions arise:

(II.a) Where are the stable points (i.e. the possible final states) in the model and which variables affect these in what way?

(II.b) How does the social model affect the diffusion of new technologies?

These research questions are of particular interest to the Rijksuniversiteit Groningen, which has made two of its three main spearhead priorities relevant to energy and environment, focusing on “Energy” and a “Sustainable Society”1. The final result of this thesis would help to introduce energy-efficient technologies in such a way that society as a whole will adopt them, rendering forceful intervention such as the E.U. “ban on bulbs” obsolete.

In this thesis, I will examine the implementation of a fully-functional multi-agent system for the domain of consumer lighting. Most importantly, I will focus on the technical aspects: the representation of knowledge, the model and its dynamics, and the implementation of same. In doing so, I will also answer the domain-specific questions which sparked this research.

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1As can be found on the university website: http://www.rug.nl/research/priorities/
Chapter 2

Agent-based modelling and the Consumat approach

2.1 Agent-based modelling

In this chapter, I will introduce the practise of multi-agent modelling, show some of its history and successes and discuss the scientific validity of this tool. After this, the Consumat multi-agent model is discussed more deeply, looking into its formation and formalisation.

2.1.1 History of agent-based modelling

The first proof-of-concept of an artificial agent likely were the “self-reproducing automata” of mathematician John Von Neumann [8], a formalisation of how a machine processing information could at the same time create a copy of itself and the instructions. This process is remarkably similar to the way in which our cells replicate DNA-strands and is thought of as the first formalisation of the requirements of self-replication.

Interestingly, Von Neumann was also closely involved in the creation and application of one of the first usages of computer simulation for research. In 1939, a letter signed by Albert Einstein was sent to the president of the United States of America warning against the possibility of an atomic weapon being developed by Hitler’s Germany and suggesting the USA start research into this new type of weapon immediately. As a result, some the the country’s leading physicists were gathered, including Oppenheimer (whom this project would make infamous), Richard Feynman, and John von Neumann to study and build this atomic weapon. During this project, Von Neumann created a model of
nuclear detonations (specifically implosions) which was used to run simulations on IBM punched-card machines; in parallel to having the regular “computers” (which were, at that time, groups of women calculating) doing the computations also. Feynman is even said to have started a competition between the two factions, resulting in the winning of the IBM machines due to their indefatigability.

One of the first multi-agent simulations occurred a rough 30 years later and was a demonstration on the dynamics of segregation by Thomas Schelling [9]. In Figures 2.1 and 2.2 we can see a visualisation of this simulation. Interestingly, the simulation was carried out with graph paper and coins initially; not on a computer, showing how much of an investment a computer for research actually was. The model however was fully functional, which later did allow for easy transfer to a computer. The model employs a concept of an agent (even though the word “agent” was not used at the time) which has a certain happiness factor and can take actions. The assumption of the model is that an agent is happiest surrounded by peers and when unhappy, it would move. This leads to behaviour as can be seen in the illustrations 2.1 and 2.2.

![Figure 2.1: An initial (randomised) state of Schelling’s simulation. Figure taken from [9].](image1)

![Figure 2.2: A final state of Schelling’s simulation, after repeatedly applying a set of rules. Figure taken from [9].](image2)
2.1.2 Recent usage

Multi-agent system simulations did not really take off until the availability of computers became more widespread. Experiencing a boost in the early nineties, when household computers had become not only viable but also affordable, multi-agent simulations have become a useful tool in studying complex dynamics, notably in sociology and economics.

An often-cited example of multi-agent research is a social simulation of an North-American Indian population over more than 500 years [10] in a particular valley, known informally as the “artificial Anasazi” (after the tribe name). In this model the population growth and clustering of a group of people was simulated over the course of years, looking at the mutual effects of environmental conditions and population size. The goal was to study the evolution and eventual decline of settlements in this valley, trying to examine the contributing factors. A result of the simulation as compared to the actual historic population (as taken from [10]) can be seen in Figure 2.3.

![Figure 2.3](image.png)

**Figure 2.3:** The best fitting simulation run of the artificial Anasazi research. The red line represents the actual historic data; the black line the simulation prediction. Figure taken from [10].

This research shows that it is possible to recreate historic data using formalised conditions to study both the data and the conditions. Of course, computer models can approximate any random graph without actually needing to have predictive or explanatory power. Underlying a model are always biased assumptions about which forces influence the agents in the model and should thus be incorporated into the model. Assumptions also need to be made about the rationality of agent behaviour and the criteria used for
Chapter 2. Agent-based modelling and the Consumat approach

Another field that has embraced multi-agent simulations is that of economics. Creators of financial models have the advantage that part of their model - the economic environment - inherently consists of numbers and formulae, which are easily captured in computer simulations. Difficulty lies in formalising how a rational, though limited, agent (such as we like to view ourselves) behaves in such an environment. Closely interwoven with game theory, game theorists have shown rational software agents are capable of playing the games of finance (e.g. the work of Sarit Kraus [11, 12]).

2.1.3 Conclusions

Multi-agent research is a branch of (computer) model simulation and has been used in various research fields successfully. By design, a model consists of (often difficult-to-test) assumptions about the dynamics incorporated. This makes it a dangerous tool for analysis and especially prediction. However, when used correctly it can be used to study the effects of variables normally beyond the researcher’s control and has been shown to be capable of accurately recreating results found in the real world based on real-world dynamics.

An important observation by W. Jager [3] is the following:

“Despite the different approaches, all models that have been developed share one essential property: the inherent impossibility to make accurate predictions for long-term future developments, no matter the level of detail in the model. This is caused by the complexity of systems involving ecology and human behaviour, which confronts us with the fundamental limits of predicting future system behaviour. Notwithstanding these serious limitations of integrated models, they can help us to show the interdependence of the various activities and their consequences in time, place and scale.”

We can see this same message in the preface of Gilbert’s and Troitzsch’s “Simulation for the Social Scientist” [13]:

“We emphasise that simulation needs to be a theory-guided enterprise and that the results of simulation will often be the development of explanations, rather than the prediction of specific outcomes.”
Chapter 2. *Agent-based modelling and the Consumat approach*

Having shown a short history of computer modelling in general and agent-based modelling in particular and some examples of their successful usage in research while also pointing out some limitations and caveats, we will now look at the model I will be using in this thesis.

2.2 The Consumat multi-agent model

I will now focus on the model used in this thesis to simulate consumer behaviour. To reiterate, the Consumat model was introduced by W. Jager in his PhD thesis \[3\] and has been adapted by M. Janssen and W. Jager to form the Consumat II model \[1\]. In this section, the underlying assumptions and dynamics of the model will be discussed. Sections of this can be seen as a summary of Jager’s thesis.

2.2.1 Theoretical foundations of the Consumat concept

The Consumat model is based on several psychological models and concepts. In this section, I will discuss the most important ones.

The Consumat model is based on four macro-level driving forces of human behaviour:

- Needs and values;
- Opportunities;
- Abilities;
- Uncertainty.

2.2.1.1 Needs and values

Author Terry Pratchett once\(^1\) wrote “all things strive”. Certainly this is the case for human beings. The American psychologist Maslow, who is best known for his hierarchy of needs \[14\], concluded that “man is a perpetually wanting animal”. This hierarchy of needs is the basis of many psychological theories of human motivation. The visual model is included as Figure 2.4.

A main influence for the Consumat model has been the human development model of Max-Neef \[16\]. He identified nine basic human needs: (1) subsistence; (2) protection; (3) affection; (4) understanding; (5) participation; (6) leisure; (7) creation; (8) identity and

(9) freedom. Because including all these needs would lead to a very complex dynamic and because formalising many of these needs would be practically impossible, the needs of the Consumat try to capture the essence of the human needs. Depending on the application, more needs could be added to the base model.

Values in this context are defined as relatively stable beliefs about the desirability of behaviours. In an unstable environment, a person’s values are more likely to change also. A person’s culture type according to the Cultural Theory [17] also is an indication of a person’s values. Cultural Theory categorises individuals in five groups which differ in their need for external restrictions and group involvement. Jager uses one of these axes, the group involvement, to separate people into either individually focused or group focused classes (as will be seen later on in Figure 2.5).

2.2.1.2 Opportunities and abilities

Obviously we must have the ability and opportunity to satisfy the needs we have. An opportunity is intuitively defined as exactly that: a possible way to satisfy one or multiple need(s). Max-Neef also speaks of opportunities and satisfiers in conjunction to the needs discussed above. Jager proposes that motivation stems from the (perceived) satisfaction an opportunity will grant.
In conjunction with opportunities we have abilities, which are the requirements we need to fulfil to make use of opportunities. These abilities may be physical, permitted/licensed, financial or social/cognitive.

2.2.1.3 Uncertainty

Lastly, uncertainty influences people’s actions to a certain degree. Because we cannot know the actual outcome of taking advantage of an opportunity before we do so and because we are always subject to unknown future developments, we cannot deterministically choose the best course of action. This uncertainty is more or less the same for everybody, but people can have a different tolerance for it. This can lead to more or less risk-taking. People with a low uncertainty tolerance would favour low-yielding but safe opportunities whereas more uncertainty-tolerant people could try more risky behavioural options.

2.2.1.4 Combining the driving forces into Consumat

These four macro-level driving forces are combined into the Consumat model through two abstractions. Jager defines *behavioural control* as the balance between the abilities someone has and the abilities demanded by some opportunity. Low behavioural control thus means an agent cannot (or can with great difficulty) take advantage of an opportunity because of some lack in abilities. Jager also defines the *level of needs satisfaction* as a combination of need and satisfaction from previously taken opportunities. A low level of satisfaction for some need means an agent is very unhappy with regards to that need and is very motivated to change this. Together with *uncertainty tolerance*, these are the basics of the Consumat model.

Making an informed decision for opportunities takes time and other resources. If the expected satisfaction gain or loss of an opportunity is not high enough, we may not want to invest much in deciding to either take or not take it. Jager uses his newly defined concepts of the level of needs satisfaction and behavioural control to discuss in which situations people are inclined to invest in optimising their opportunity usage.

When someone is generally happy with the current state of affairs, id est, has a high level of needs satisfaction and their behavioural control is not endangered (due to increasing prices, for example), they can afford to continue doing what they generally do with little or no thought. Jager calls this “automated processing”: choosing some action using very simple heuristics and with little thought. But should for some reason the satisfaction level drop or the “normal” course of action become unattainable, it could
be very profitable to make a more informed decision. This “informed processing” as Jager calls it is more resource-consuming than automated processing but has a higher potential for a change in needs fulfilment.

Jager also makes a distinction between “individual processing” and “social processing”. If we look solely at our own needs and options and decide what to do based on that, this is individual processing. We are more likely to engage in this behaviour if we are relatively certain of the availability and outcome of our opportunities and if the needs we are trying to fulfil are more personal. The opposite of this is social processing, which means incorporating observations and expectations of the behaviour of others into our individual reasoning. If we are more uncertain or are trying to fulfil a general need, we are more likely to look to others to see what we could (and perhaps should) do.

Social aspects also play a large role in human decision making. To capture this, Social Theory is used by Jager. Using cultural perspective as outlined by the Social Theory archetypes to indicate willingness and need of people to belong to groups, he partitions people along one Cultural Theory-axis into people who are not sensitive to group opinions versus people who are. Figure 2.5 shows the Consumat model based on these concepts together with the psychological models they cover.

<table>
<thead>
<tr>
<th>Individually determined</th>
<th>Repetition</th>
<th>Deliberation</th>
</tr>
</thead>
<tbody>
<tr>
<td>High level of need satisfaction; high behavioural control</td>
<td>- Classical conditioning theory</td>
<td>- Decision and choice theory</td>
</tr>
<tr>
<td>- Operant conditioning theory</td>
<td>- Theory of reasoned/planned behaviour (attitude and perceived control)</td>
<td></td>
</tr>
<tr>
<td>Social determined</td>
<td>Imitation</td>
<td>Social comparison</td>
</tr>
<tr>
<td>- Social learning theory</td>
<td>- Social comparison theory</td>
<td>- Social comparison theory</td>
</tr>
<tr>
<td>- Theory of normative conduct</td>
<td>- Relative deprivation theory</td>
<td>- Relative deprivation theory</td>
</tr>
<tr>
<td></td>
<td>- Theory of reasoned/planned behaviour (social norm)</td>
<td>- Theory of reasoned/planned behaviour (social norm)</td>
</tr>
</tbody>
</table>

Figure 2.5: A table showing Jager’s Consumat model partitioned in the terms he uses. The boxes show which psychological theories explain the behaviour. Figure taken from [3] and slightly adapted for clarity.

2.2.1.5 Conclusions

Figure 2.5 shows the theoretical basis of Consumat and the psychological theories which help explain the behaviour as modelled by it. In this section I have discussed the main psychological sources and theories used to develop the concept of Consumat. In the next section, we will look at the formalisation of Consumat.
2.2.2 Generic formalisation of Consumat

In this section, I will discuss the generic formalisation of the Consumat II model. The basis for this is a paper by Jager and Janssen in which the Consumat II model is presented [1]. The following section can be seen as a summary of this paper.

2.2.2.1 Aspects of the formal Consumat

First and foremost, the Consumat needs to define a satisfaction level for its needs. To formalise need satisfaction, each need must be described as some action with a need-fulfilling satisfaction utility level and possibly associated action costs. Each individual Consumat agent also needs an aspiration level to formalise when it is contented with its satisfaction level. Comparing the aspiration for each need with its current satisfaction level will lead to some discrepancy, which, in turn combined with the utility for certain actions, will result in a certain motivation for performing actions. The Consumat also experiences utility uncertainty and social uncertainty. For both of these uncertainties it also has an individual uncertainty tolerance.

For each of these variables, a mathematical description must be given. From these aspects, the Consumat behaviour follows. The most important driving forces are the ratio of aspiration level versus satisfaction level and the ratio between the uncertainty and the uncertainty tolerance.

Many of these variables are application-dependent, meaning no general description can be given without considering the field of application. Below are some aspects for which a generic formalisation is possible.

2.2.2.2 Needs and need satisfaction

The first Consumat model defined the level of need satisfaction (LNS) as a number between 0 and 1 using the following formula:

\[ LNS_{it} = 1 - \exp(-\alpha \cdot o_j) \]

In this formula, \( LNS_{it} \) stands for the level of need satisfaction for need \( i \) at time \( t \). The parameter \( \alpha \) indicates the sensitivity for the consumption of opportunity \( o_j \).

For the Consumat II model, this satisfaction level was adjusted to better suit a rational agent which is capable of planning. For example, in a time of plenty, a survivalist
agent need not have a large food storage to be satisfied in terms of its existence. But if the agent expects (e.g.) a seven year drought, a small supply of food would not be satisfactory. This means that the expectations of the future satisfaction can have an impact on current satisfaction. Obviously, the time length to factor in is not constant over needs, as some needs (such as fashion-dependent ones) are by nature short-term satisfiable only.

To formalise this, Janssen and Jager introduce a discount formula into the need satisfaction formula.

\[
LNS(N_x, o, t) = \sum_{i=t}^{m} f(i) \cdot NU(N_x, o, i), \quad m \geq t
\]

In this formula, \(LNS(N_x, o, t)\) is the level of need satisfaction of need \(N_x\) provided by utilising opportunity \(o\) at time \(t\). The value \(NU(N_x, o, t)\) is the need utility of need \(N_x\) provided by opportunity \(o\) at time \(t\). The discounting is realised through function \(f(t)\), which (usually) is a decaying function over time. If \(f(t)\) declines steeply, the Consumat II will not be particularly interested in the future for determining its current level of need satisfaction. If \(f(t)\) slowly declines, the Consumat II will value its predictions about future satisfaction in considering whether its current needs are met.

### 2.2.2.3 Uncertainty

In the previous section, the Consumat II agent is expected to predict its utility \(NU\) at any time \(t\). These predictions need not come true and thus the Consumat II experiences uncertainty. If an agent receives conflicting information about its future utilities from different sources, the agent will experience more uncertainty. If all indications of the future utility are similar, the agent will be more sure. This we can express as the variance between predictions:

\[
\text{Unc}(N_x, o, t) = \text{Var}(NU_i(N_x, o, t))
\]

Similarly, an agent can be uncertain about its social needs. In this case, the uncertainty can be expressed as the variance in the action choices of similar agents. If these peers choose different actions, the Consumat II will be less certain of choosing a socially good action.

In the implementation of the Consumat for the lighting market, this “uncertainty” aspect of the Consumat will be replaced by a “social satisfaction” level as second axis to be
used alongside the subsistence need satisfaction level. In the original model, a Consumat agent chooses to rely on social aspects because of an uncertain future. In this specific implementation, a Consumat agent chooses to rely on social aspects because it perceives it is unlike the majority of the population. In the case of the lighting market, this “short cut” is sufficient to represent the uncertainty an agent experiences which may cause it to adopt social strategies.

2.2.2.4 Heterogeneity

The heterogeneity of agents is also important in the multi-agent model, especially noting the uncertainty tolerance and the ambition level. Varying these characteristics results in different types of agents, each playing a different role in the adoption of new technologies. It may be necessary or at least helpful for marketing purposes to know about and possibly target a specific section of the population to promote early adoption.

2.2.2.5 Conclusions

The need satisfaction and uncertainty of the Consumat II model can be expressed in general formulae. Many of the necessary variables however are not (yet) generally expressible but need to be formulated with the field of application in mind. In the next chapter, the field of application for this study will be discussed and an attempt will be made to fully formalise the Consumat II model for this specific purpose.
Chapter 3

Implementation of the Consumat model

In this chapter, the implementation choices for the Consumat model for the lighting market will be discussed. In the first section, the Consumat model as explained in the previous chapter will be summarised very briefly. After this, the modelled characteristics are discussed. Lastly, all the dynamics in the model are defined.

3.1 Consumat summary

The Consumat is an abstraction of a consumer, which has needs and aims toward fulfilling these needs by taking one of four decision processes:

1. Repetition: ignoring other options and selecting the same option as before;
2. Imitation: looking at peers and selecting one of their choices;
3. Enquiring: considering the choices of all other Consumat agents as an option;
4. Optimisation: considering all possible options and making an informed decision.

Each time an action is needed, the Consumat engages on one of these decision processes based on its existential needs, social needs and satisfaction as shown in Table 3.1. This choice is not fully deterministic, because the determination of social satisfaction depends on a Monte-Carlo estimate of similarity to peers (3.5.3). Other than this, the process does not have a stochastic nature: if for example the threshold for functional satisfaction
Table 3.1: Behaviour of the Consumat related to the level of functional satisfaction and the level of social satisfaction. The symbols $\theta_s$ and $\theta_f$ stand for an agent-specific social and functional threshold, respectively.

<table>
<thead>
<tr>
<th>Functional satisfaction</th>
<th>Social satisfaction</th>
<th>Repetition</th>
<th>Imitation</th>
<th>Optimising</th>
<th>Enquiring</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\geq \theta_f$</td>
<td>$\geq \theta_s$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$&lt; \theta_f$</td>
<td>$&lt; \theta_s$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

has been reached and an agent is “functionally content”, it will never engage in a decision process which requires low functional satisfaction.

The definitions of “subsistence satisfaction” and “social satisfaction” can be found in Sections 3.6.1 and 3.6.2 respectively; the implementation of the four decision processes can be found in Section 3.7.

### 3.2 Lamp properties

#### 3.2.1 Modelled lamp properties

For the formal model of the lighting market, the following characteristics will be incorporated to describe an individual light source.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value space</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>LED/CFL/incandescent</td>
<td>Type of lamp</td>
</tr>
<tr>
<td>Price</td>
<td>integer (euro)</td>
<td>Purchasing price</td>
</tr>
<tr>
<td>Energy efficiency</td>
<td>A/B/C/D/E/F/G</td>
<td>Energy efficiency based on European Union label scale</td>
</tr>
<tr>
<td>Colour discrepancy</td>
<td>integer (percent)</td>
<td>Deviation in colour</td>
</tr>
<tr>
<td>Ramp-up time</td>
<td>integer (seconds)</td>
<td>Time it takes for the lamp to get to full strength</td>
</tr>
<tr>
<td>Life expectancy</td>
<td>integer (months)</td>
<td>Average expected life time of the lamp</td>
</tr>
</tbody>
</table>
All of these aspects apart from Type are dynamic: they may change during the simulation.

### 3.2.2 Trait details

The inclusion of the Type, Price, Ramp-up time and Life expectancy characteristics are because these are measurable properties of a light bulb that directly influence the consumer’s choices.

The Energy efficiency is an A-G rating that is mandatory within the European Union\(^1\); an example can be seen in Fig. 3.1.

The Colour discrepancy characteristic exists to coincide with one of the agent properties discussed in the next section and is used to address the preference agents have towards the colour of lights. This property is the only “artificial” one: in the sense that this isn’t something that can be measured from the lamp itself but instead is a subjective appreciation of the light.

![Europian Energy Efficiency](http://www.labelinfo.be/label/lange_fiche/978/)

**Figure 3.1:** EU label for energy efficiency of lamps showing an A-G scale. Image taken from [http://www.labelinfo.be/label/lange_fiche/978/](http://www.labelinfo.be/label/lange_fiche/978/).

### 3.2.3 Trait dynamics

The dynamic lamp properties (which are all lamp properties except Type) can be altered during the run of the model. This is not a part of the model, but a possible way to influence the model run by changing parameters. This allows the modeller to incorporate technological advances, price drops and other market developments for hypothetical simulation runs.

3.3 Agent properties

3.3.1 Introduction

The properties of the Consumat agent below have been based on a 2012 survey \cite{2} in which consumers were asked about their preferences concerning lighting. The values later assigned to these traits will be based on this survey as well. In the next chapter, this survey will be discussed more in-depth together with the parametrisation of the model.

3.3.2 Modelled agent properties

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value space</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subsistence flexibility</td>
<td>integer (percent)</td>
<td>Level of task unsuitability an agent accepts</td>
</tr>
<tr>
<td>Colour flexibility</td>
<td>integer (percent)</td>
<td>Level of colour discrepancy an agent accepts</td>
</tr>
<tr>
<td>Energy focus</td>
<td>integer (percent)</td>
<td>Focus an agent has on energy consumption</td>
</tr>
<tr>
<td>Usage focus</td>
<td>integer (percent)</td>
<td>Focus an agent has on environmental issues</td>
</tr>
<tr>
<td>Social flexibility</td>
<td>integer (percent)</td>
<td>Level of social distance an agent is willing to accept</td>
</tr>
<tr>
<td>Social agreeability</td>
<td>integer (percent)</td>
<td>Level of social conformity</td>
</tr>
<tr>
<td>Experience</td>
<td>integers (percent)</td>
<td>Amount of positive experience with different lighting types</td>
</tr>
<tr>
<td>Atmosphere requirements</td>
<td>integer (amount)</td>
<td>Number of atmosphere lights the agents needs</td>
</tr>
<tr>
<td>Functional requirements</td>
<td>integer (amount)</td>
<td>Number of functional lights the agents needs</td>
</tr>
</tbody>
</table>

In the model, only the \textit{Experience} characteristic is dynamic.
3.3.3 Trait details

The *Subsistence flexibility* is the quality used to describe what level of subsistence satisfaction an agent is willing to accept to be content. This is used to determine the actions of an agent when selecting a new lamp as directed by the Consumat model. The higher this number, the easier it is to satisfy the agent.

The *Colour flexibility* is used to indicate how strict an agent is when selecting a new lamp in regard to colour expectancy. A higher number indicates the agent is willing to accept a higher light colour discrepancy. In Section 3.6.3 will be shown how this value is used to calculate agent satisfaction.

The *Energy focus* and *Usage focus* both show how interested the agent is in energy consumption of lamps, but differ in that the first trait has to do with purely financial motives, whereas the second has to do with purely environmental sentiments. This is an important distinction, because based on other considerations (such as the purchasing price) an agent that is focussed on energy usage because of the price of electricity may still decide to pick a wasteful lamp, whereas those considerations are not that important to someone primarily interested in the environment. The more interested an agent is in either type, the higher this value becomes. In Section 3.6.3 will be shown how these values are used to calculate agent satisfaction.

The *Social flexibility* trait is the second Consumat property (*Subsistence flexibility* being the first) which determines how high an agent’s satisfaction needs to be for the agent to be content; in this case about its social needs. The higher this number, the easier it is to satisfy the agent.

*Social agreeability* encodes an agent’s desire to be a part of a group. If this number is high, the agent prefers to move with the crowd. If the number is low, an agent prefers to set itself apart from the group. An agent with a high degree of *Social agreeability* will be more conformist. An agent with low *Social agreeability* will instead be anti-conformist. This may be an important aspect to explain the behaviour of early adopters.

The *Experience* quality is actually a vector of values: for each type of lamp (LED/Halogen/CFL/incandescent) each agent has a corresponding experience characteristic to show its opinion of this type of light. These traits are the only dynamic traits of an agent: only these values change during the run of a simulation. The higher each number, the better an agent thinks of that particular type of lighting.

The *Atmosphere requirements* and *Functional requirements* simply encode the number of atmospheric and functional lamps an agent requires. The different types of lighting an agent needs - atmospheric and functional - are to show the different usage lamps
have in a household. The choice of lamps in living areas is more largely influenced by atmospheric considerations, meaning they must fulfil a higher aesthetic component. Functional lamps, such as desk lamps or attic lamps, are evaluated more in terms of their functional aspects.

### 3.3.4 Trait dynamics

As mentioned before, only the *Experience* characteristic is dynamic. This means that all other values will not be changed during the simulation. The experience an agent has with the types of lighting will be influenced by direct experience and observation through peers.

At the time a lamp breaks, the *Experience* of the owner is updated. This is described in Section 3.4.2. When an agent has contact with a different agent, experiences are also updated. This is described in Section 3.5.2.

### 3.4 Lamp replacement dynamics

Agents only choose a new lamp when one of their current lamps break. The lifetime, experience update process and replacement choice mechanism is describes in this section.

#### 3.4.1 Lifetime determination

Each agent has a total of *Atmosphere requirements* + *Functional requirements* lamps in his possession at any one time. A lamp is represented by its *id*, by which we know what kind of lamp it is, and a *lifetime*. This lifetime is determined at the time of creation by drawing it from a normal distribution around its *Life expectancy* trait. Every iteration, this lifetime is decremented. Once the lifetime reaches zero, the lamp breaks and will be replaced immediately.

Immediate replacement with a new lamp may not be fully realistic, because it is quite possible a broken lamp goes unreplaced for a period of time by force majeure, indifference or other factors. In the model, the assumption is made that every broken lamp will be replaced eventually and the time difference between breaking and replacement is not significant. This allows for a simpler model.

Lamp lifetime is not a component in any other part of the model. Yet the lifetime has a not to be overlooked impact on which lamps have the highest occurrence in the model, simply because a lamp is only replaced when it breaks. Lamps with a higher life time
will thus be less easily replaced than lamps with a shorter lifetime and thus remain in possession of the agent longer.

### 3.4.2 Experience update

The experience update caused by the broken lamp is based on the *Lamp satisfaction*. The “Lamp satisfaction” used here is a function of the broken lamp, differs slightly for functional and atmospheric lamps and can be found in Section 3.6.3. In short this means that a lower colour discrepancy, higher energy efficiency lower ramp-up time and lower price are preferred. The difference in experience and satisfaction is calculated:

\[
\Delta \text{Experience} = \text{Lamp satisfaction} - \text{Experience}
\]

Note that this difference may very well be negative. The actual update is performed using a weight parameter \( w \) ranging from zero to one:

\[
\text{Experience} = \text{Experience} + \Delta \text{Experience} \times w.
\]

### 3.4.3 Choice of replacement

The choice of a replacement lamp is based on the Consumat dynamics. For ease of notation, *Subsistence rigour* is defined as \( 100 - \text{Social flexibility} \) and *Social rigour* is defined as \( 100 - \text{Social flexibility} \).

There are four possible decision processes for an agent to engage in:

Chapter 3. Implementation of the Consumat model

4. *Subsistence rigour* \(\geq\) subsistence satisfaction, *Social rigour* \(\geq\) social satisfaction:

Enquiring.

The definition of “subsistence satisfaction” can be found in Section 3.6.1, the definition of “social satisfaction” can be found in Section 3.6.2 and the implementation of the four decision processes can be found in Section 3.7.

3.5 Inter-agent dynamics

In this section, the dynamics of agent interaction are described.

3.5.1 Frequency of agent interaction

During the simulation, an agent can have social contacts which influence its *Experience* traits. Frequency of social encounters is determined by a constant model parameter, the *Social Frequency*, which holds the chance in percentages of a social encounter for a single agent in a single time step. If, for example, the *Social Frequency* is set to “2”, every agent has a two-percent chance of a social encounter per time step, meaning that in a simulation with 1000 agents, on average 20 social contacts occur per time step. Due to the stochastic nature of this event, it is possible that no social contact occurs during a time step.

3.5.2 Dynamics of agent interaction

At the moment of interaction, the first step is to decide with which other agent (the “interactee”) the interacting agent (the “initiator”) will have contact. The interactee is chosen by a stochastic process with a preference towards agents similar to the initiator agent. A maximum difference between agents is defined. Then an agent is randomly chosen from the pool of all agents. If the difference, in this case defined as the sum of the differences of every agent property, between the initiator and the candidate interactee is smaller than or equal to the maximum difference, the candidate is selected for social interaction. If the candidate differs too much from the initiator, the maximum difference is incremented and a new random agent is drawn. It is impossible for an agent to interact with itself.

This selection process means that the probability of interaction is a function of similarity: it is more likely for agents to have contact with similar agents, but not impossible for agents to have contact with very dissimilar ones.
After the interactee has been selected, the Experience values of the initiator are adjusted based on the Experience values of the interactee and the Social traits of the initiator. The formula used is:

\[ \Delta \text{Experience} = \text{interactee Experience} - \text{initiator Experience} \]

\[ \text{Weight} = \frac{\text{initiator Social agreeability} - 50}{100} \]

\[ \text{initiator Experience} = \text{initiator Experience} + \Delta \text{Experience} \times \text{Weight} \]

\( \Delta \text{Experience} \) is a vector containing the differences between the Experience values of the two agents. The Weight variable is a value between \(-0.5\) and \(+0.5\) which is used to scale the update. Note that the direction and amplitude of the update depends on the difference between the agent’s Experiences and the Social agreeability of the initiator.

### 3.5.3 Inter-agent difference

The inter-agent difference is used to calculate the social satisfaction of agents, which in turn is based on the level of similarity between agents. This difference is a number between zero and one hundred which indicates to which extent an agent is similar to its peers. Every agent thus has its own inter-agent difference.

The only character trait important for the difference is the Experience vector of agents. This difference is computed by calculating the difference between every data point in the vector and summing the results together. Because the number of data points in the Experience vector is equal to the number of lamp types in the model, the inter-agent difference can range from 0 to 100 \(\times\) (\# lamp types).

Because it is unreasonable to scale this inter-agent difference assuming the theoretical maximum of a difference of 100, a smaller value Assumed Maximum will be chosen as an assumed maximum. This value can be found in Section 4.5.7. The final scaling will be done using this formula:

\[ \text{Scaled difference} = \frac{\text{Inter-agent Difference} \times 100}{\# \text{lamp types} \times \text{Assumed Maximum}} \]

The similarity is thus estimated based on a randomly chosen section of the population.
3.6 Intra-agent dynamics

In this section, the inner workings of agents are described.

3.6.1 Subsistence satisfaction

The subsistence satisfaction of an agent is determined by and equal to the values of the *Experience* characteristic of an agent. This is vital, because the *Experience* is the only dynamic property of an agent. This also means that an agent does not have a single subsistence satisfaction, but in fact has separate satisfaction levels for every type of light.

For completeness, the formula for subsistence satisfaction is given below:

\[
\text{Subsistence satisfaction} = \text{Experience}
\]

3.6.2 Social satisfaction

The social satisfaction of an agent is determined by its similarity to other agents. In general, a social agent will be more content if it is more similar to the group. Because agents can also have anti-conformist tendencies as encoded in the *Social Agreeability* trait, it seems reasonable those agents will be happier when the distance between them and the group is larger. Because we do not want to limit social satisfaction by using the *Social Agreeability* trait to scale it, it will only be used to provide the direction of the correlation with inter-agent differences, not the amplitude.

The average similarity to other agents in the model is determined through a Monte-Carlo estimation. This method is chosen because a full comparison was too costly. A pre-determined portion of the total population will be randomly selected to be compared to the current agent. This portion is controlled by a parameter *Monte-Carlo sample size*. This value can found in Section 4.5.8. The average difference between the current agent and randomly selected peers will be the used as the *Inter-agent difference*.

\[
\text{Satisfaction} = \begin{cases} 
100 - \text{Inter-agent difference} & \text{if Social Agreeability} \geq 50 \\
\text{Inter-agent difference} & \text{otherwise}
\end{cases}
\]
3.6.3 Lamp satisfaction

Subsistence satisfaction is defined per lamp and differs in parameter values whether the agent expects the lamp to perform a functional or atmospheric role. For subsistence satisfaction, the following general formula is used:

\[ 	ext{Lamp satisfaction} = a_1(\text{Colour Flexibility} - \text{Colour Discrepancy}) + a_2(\text{Energy Efficiency} - \text{Focus Energy}) + a_3(\text{Energy Efficiency} - \text{Focus Usage}) + a_4(-\text{Ramp up Time}) + a_5(-\text{Price}) \]

[– Note: This formula proved to be inadequate for the final model. This is explained in Chapter 6 and the lamp satisfaction formula used in the final model can be found in Section 6.4. For administrative reasons, the original formula is maintained here. End note. –]

The parameters \(a_1\) through \(a_5\) will have different values depending on whether the lamp being evaluated is a functional lamp or an atmospheric lamp. The values of these parameters can be found in Sections 4.5.9 and 4.5.10.

The result of this formula is not within the 0-100 percent range, but is scaled to this range using the lowest (Lowest) and highest (Highest) theoretical outcome:

\[ 	ext{Scaled satisfaction} = \frac{(\text{Lamp satisfaction} - \text{Lowest}) \times 100}{\text{Highest} - \text{Lowest}} \]

3.7 Agent decision processes

In Section 3.4.3, the behaviour selection procedure can be found that determines which decision process an agent will engage in. Below the implementations of the four decision processes are defined.
3.7.1 Repetition

The broken lamp is replaced with exactly the same type. The agent will not inspect the new lamp, so it may be the case (because lamp characteristics may be altered during a run) an agent will select a now less suitable lamp.

3.7.2 Imitation

The agent will select one of its closest peers using the “interactee” selection procedure outlined in Section 3.5.2. Next, a conformist agent (defined by $Social\ Agreeability \geq 50$) will randomly pick a lamp of the inventory of this other agent. An anti-conformist agent (defined by $Social\ Agreeability < 50$) will randomly pick any lamp not in the inventory of this other agent. If such a lamp does not exist (because the other agent happens to have every type of lamp), a random lamp is chosen.

3.7.3 Optimisation

The agent looks at all available lamps and selects the best lamp using the lamp satisfaction function described in Section 3.6.3.

3.7.4 Enquiring

The agent will select one of its closest peers using the “interactee” selection procedure outlined in Section 3.5.2. Next, a conformist agent (defined by $Social\ Agreeability \geq 50$) will select the best lamp from the other agent’s inventory using the lamp satisfaction function described in Section 3.6.3. An anti-conformist agent (defined by $Social\ Agreeability < 50$) will pick the best lamp not in the inventory of this other agent. If such a lamp does not exist, the anti-conformist agent defaults to the optimisation action.
Chapter 4

Model parametrisation: methods and results

In the previous chapter, the implementation of the Consumat model (from now on simply “model”) has been discussed. In this model, a number of parameters have been left unassigned. In addition to this, the question of how to initialise the agents and lamps in the model has been left undiscussed. In this chapter, every initial value in the model will be defined. The data on which these values are based will be introduced, the methods for processing explained and the final results shown.

4.1 Model parameters

Every model parameter is listed below for clarity. In the following sections, we will assign each of these a proper value.

4.1.1 Lamps

- The number of individual lamps on the model
- The initial characteristics of each lamp (3.2.1):
  - Type
  - Price
  - Energy efficiency
  - Colour discrepancy
  - Ramp-up time
4.1.2 Agents

- The number of individual agents in the model

- The initial characteristics of each agent (3.3.2):
  - Subsistence flexibility
  - Colour flexibility
  - Energy focus
  - Usage focus
  - Social flexibility
  - Social agreeability
  - Experience (vector)
  - Atmosphere requirements
  - Functional requirements

- Experience update weight $w$ (3.4.2)

- Social Frequency of social interaction (3.5.1)

- Assumed Maximum of inter-agent difference (3.5.3)

- Monte-Carlo sample size of social satisfaction (3.6.2)

- Functional lamp satisfaction parameters $a_1$-$a_5$ (3.6.3)

- Atmospheric lamp satisfaction parameters $a_1$-$a_5$ (3.6.3)

4.2 Lamp data

In this section, the methods for gathering the lamp data will be discussed.
4.2.1 Purposes and approach

For the model, a list of lamps is needed for the agents to choose from. The main concern is that this lamp data needs to be realistic. In gathering data, the focus does not lie in gathering the most accurate information, but in getting the information a consumer would also get. Because of this, we have not contacted manufacturers of lamps nor researched the statistics in scientific literature, but gathered our information from stores and their employees.

4.2.2 Questions

The following questions need to be answered:

- Which types of lamps are available to the general consumer?
- For each of these types:
  - Roughly how many different lamps of this type are available to the general consumer?
  - What are the characteristics (price, energy efficiency, colour discrepancy, ramp-up time and life expectancy) of these lamps?

The ideal is to get a number of lamps for each type which is roughly proportional to what is available in the stores.

4.2.3 Methods

In November and December of 2013, several stores were visited: a supermarket, a DIY-store, a general supplies store, and a specialist lamp store. This was done in the Netherlands. In these stores, the different types of lamps available were noted. In case of absence of one or more needed characteristics, employees were asked. During this, the researcher did not disclose the purpose of the questions and simply pretended to be an interested customer.

4.2.4 Results

Both the raw data and the distilled information to be used in the model has been included as appendices.
Chapter 4. Model parametrisation

4.3 Normal distribution for lamp lifetime

When determining the lifetime of a modelled lamp, it is drawn from a normal distribution with $\mu = \text{Life expectancy}$ and $\sigma = \frac{\mu}{5}$. This means there is roughly an 68 percent likelihood of the lifetime being the range $0.9\mu$ to $1.1\mu$, roughly 95 percent chance of it being within $0.8\mu$ to $1.2\mu$, and roughly 99.7 percent chance of it being within $0.7\mu$ to $1.3\mu$.

Fig. 4.1 and Fig. 4.2 are two examples of the normal distribution for different lifetime expectancies.

4.4 The number of agents

By default, the runs of the model will have 1000 agents. If this number is varied during an experiment, this will always be clearly indicated.

4.5 Agent characteristics parametrisation

For the initial values for the agent characteristics, a study has been used in which subjects were asked about their lighting preferences. Questions from this survey were selected to provide realistic data to initialise the model. In the following section, the data, the selected questions and the pre-processing actions will be explained, which will result in evidence-based initial values for the agent’s characteristics.
4.5.1 Data source

As a data source, the survey results from a 2012 Master’s thesis will be used [2]. This thesis questioned 97 Dutch subjects about their lamp purchase habits and considerations. After removing respondents with missing answers for the relevant questions, the resulting number of test subjects was 87.

4.5.2 Agent instantiation process

Each individual agent will be based on one of the 87 respondents. This means that the model can have, at most, 87 unique agents. To mitigate this issue, every actual agent will be instantiated based on one of our 87 ideal agents with five percent leeway for each property. This leeway is implemented by a uniform draw from the set of possible property values. For example, if one ideal agent has a colour flexibility of “76”, the value of this property for an actual agent based on this ideal one, will be uniformly drawn from the 72 to 80 range.

4.5.3 Selected survey questions

Here the selected relevant questions from the survey are reproduced. The questions were asked in Dutch to Dutch respondents, but I have translated these for the sake of the reader. Any small inaccuracies in translation do not affect the quality of the research. The questions have been given an identification label to facilitate referring to them later. These id labels are new and did not appear in the original survey.

4.5.3.1 QF1

For the following question, the respondent is asked to rate each item on a 1-7 Likert scale [18].

When choosing a plafonnière/primary room lamp, I mainly focus on:

1. The colour temperature of the light (“warm” or “cold”);
2. The degree to which colours are shown properly;
3. The light quantity;
4. The time needed to “start”/get to full strength;

\footnote{We will see this is not actually true, because the experience property is randomly initiated, but the underlying problem of low variance remains}
5. The purchasing price of a bulb;
6. The electricity costs of the light;
7. The electricity usage of the light in regards to the environment.

4.5.3.2 QF2

For the following question, the respondent is asked to select each applicable answer.

When choosing a plafonnière/primary room lamp, the deciding factor was (multiple answers possible):

1. The colour temperature of the light ("warm" or "cold");
2. The degree to which colours are shown properly;
3. The light quantity;
4. The time needed to "start"/get to full strength;
5. The purchasing price of a bulb;
6. The electricity costs of the light;
7. The electricity usage of the light in regards to the environment.

4.5.3.3 QA1

For the following question, the respondent is asked to rate each item on a 1-7 Likert scale.

When choosing a sitting room lamp, I mainly focus on:

1. The colour temperature of the light ("warm" or "cold");
2. The degree to which colours are shown properly;
3. The light quantity;
4. The time needed to "start"/get to full strength;
5. The purchasing price of a bulb;
6. The electricity costs of the light;
7. The electricity usage of the light in regards to the environment.
4.5.3.4 QA2

For the following question, the respondent is asked to select each applicable answer.

When choosing a sitting room lamp, the deciding factor was (multiple answers possible):

1. The colour temperature of the light ("warm" or "cold");
2. The degree to which colours are shown properly;
3. The light quantity;
4. The time needed to "start"/get to full strength;
5. The purchasing price of a bulb;
6. The electricity costs of the light;
7. The electricity usage of the light in regards to the environment.

4.5.3.5 QS1

For the following question, the respondent is asked to rate each item on a 1-7 Likert scale or tick "Not applicable".

How important are the opinions of the following persons when selecting a lamp?

1. Partner;
2. Children;
3. Friends;
4. Colleagues.

4.5.3.6 QS2

For the following question, the respondent is asked to rate each item on a 1-7 Likert scale.

Information about lamps reaches me primarily via:

1. Stores;
2. Internet;
3. Family;
4. Friends;
5. Television;

4.5.3.7 QS3

For the following question, the respondent is asked to rate each item on a 1-7 Likert scale.

For the following positions, indicate how much you agree with them:

1. Generally I’m the first one in my social circle who buys a new lamp when it appears;
2. If I were to learn a new type of lamp is available in stores, I’d be interested enough to purchase it;
3. Compared to my social circle, I own a large number of lamps;
4. Generally I’m the first one in my social circle who knows the types and brands of new lamps;
5. I enjoy buying new types of lamp before my social circle.

4.5.3.8 QP1

For the following question, the respondent is asked to give a number.

How many lamps do you approximately have in use?

4.5.4 Data processing

To use the answers given to the questions above in the model, the results were interpreted to assign a percentage value or a single number to every ideal agent property (Section 3.3.2). For every property, below is shown which questions were used to compute this value and the exact formula used.
4.5.4.1 Subsistence flexibility

The *subsistence flexibility* property is based on the answers to question QF1 (Section 4.5.3.1).

For question QF1 the possible replies lie in the Likert scale range from one to seven, thus the sum of the answers to these questions ranges from 7 to 49. This “reply range” denotes the range the sum of the answer values can take. The sum of the actual replies a correspondent has given for the relevant questions will be depicted by the following formula:

\[ \text{Reply} = \text{Sum}(QF1) \]

The comma-separated list in the *Sum* function shows the questions (or in this case: question) from which the answer values are taken. This value will thus, by definition, always lie within the reply range.

In the process, the reply ranges are always corrected to begin at zero by decreasing the maximum value with the minimum value. This is called the correction step. Thus, the corrected reply range for questions QF1 becomes 0 to 42. Because the corrected reply range always starts at zero, the range can be depicted by a single number. We say the corrected reply range for QF1 equals 42. The actual reply given will also be corrected thus and be denoted by the *CSum* function.

Next, the reply is converted to a percentage using the following formula:

\[ \text{Percentage} = \frac{\text{Corrected Reply} \times 100}{\text{Corrected reply range}} \]

\[ = \frac{\text{CSum}(QF1) \times 100}{42} \]

It can be seen this percentage with always have the same discrete number of values as the corrected reply range, but scaled from 0 to 100. Because in this case a higher reply indicated a more demanding consumer, the *subsistence flexibility* property is defined thus:

\[ \text{Sub. flex.} = 100 - \text{CSum}(QF1) \times \frac{100}{42} \]
4.5.4.2 Colour flexibility

The colour flexibility property is based on the answers to questions QF1.1:2\(^2\) (Section 4.5.3.1), QF2.1:2 (Section 4.5.3.2), QA1.1:2 (Section 4.5.3.3), and QA2.1:2 (Section 4.5.3.4). The corrected range for the sum of these answers is 48, giving this formula for colour flexibility:

\[
\text{Col. flex.} = 100 - C\text{Sum}(QF1.1:2, QF2.1:2, QA1.1:2, QA2.1:2) \times \frac{100}{48}
\]

4.5.4.3 Energy focus

The energy focus property is based on the answers to questions QF1.6 (Section 4.5.3.1), QF2.6 (Section 4.5.3.2), QA1.6 (Section 4.5.3.3), and QA2.6 (Section 4.5.3.4). The corrected range for the sum of these answers is 24, giving this formula for energy focus:

\[
\text{Energy focus} = C\text{Sum}(QF1.6, QF2.6, QA1.6, QA2.6) \times \frac{100}{24}
\]

4.5.4.4 Usage focus

The usage focus property is based on the answers to questions QF1.7 (Section 4.5.3.1), QF2.7 (Section 4.5.3.2), QA1.7 (Section 4.5.3.3), and QA2.7 (Section 4.5.3.4). The corrected range for the sum of these answers is 24, giving this formula for usage focus:

\[
\text{Usage focus} = C\text{Sum}(QF1.7, QF2.7, QA1.7, QA2.7) \times \frac{100}{24}
\]

4.5.4.5 Social flexibility

The social flexibility property is based on the answers to questions QS1 (Section 4.5.3.5) and QS2.3:4 (Section 4.5.3.6). This means social flexibility is defined as a function of how important the opinions of others are to the agent. If an agent deems those opinions not that important, it is more flexible. If an agent values opinions of other very highly, it is less flexible.

Because the answers to QS1 are optional, the corrected range Corrected Range can be either 12 (no answers of QS1), 18 (one answer of QS1), 24 (two answers of QS1), 30

\(^2\)The notation “QF1.1” refers to the first item of question QF1, which can be found in Section 4.5.3.1. Thus, in this case, it refers to the focus on “light temperature” when choosing a plafonnier/primary room lamp. The notation “QF1.1:3” refers to items one through three (inclusive) of question QF1.
(three answers of QS1), and 34 (all answers of QS1). The correct value will be chosen for each individual respondent, giving the following formula for social flexibility:

$$Soc. \, flex. = 100 - CSum(QS1, \, QS2.3:4) \times \frac{100}{Corrected \, Range}$$

### 4.5.4.6 Social agreeability

The social agreeability property is based on the answers to questions QS3 (Section 4.5.3.7). The “agreeability” trait is defined by “early adopter” questions on the assumption that early adopters are people more likely to deviate from established roads. This assumption may be justifiably challenged, but has been made because it was the best approach available with the data provided.

The corrected range for the sum of these answers is 30, giving this formula for social agreeability:

$$Soc. \, agreeab. = 100 - CSum(QS3) \times \frac{100}{30}$$

### 4.5.4.7 Experience

The experience property is not based on the survey answers, because suitable questions were not asked. Instead, the experience property for each lamp type is drawn from a uniform distribution in the range of 30 to 70. This range was arbitrarily chosen to allow for a wide variety in experiences, but none too extreme. It is thought extreme initial values inhibit any change during the run of the model, which this range is chosen to prevent.

### 4.5.4.8 Number of lamps: atmosphere and functional requirements

The atmosphere requirement and functional requirement properties hold the number of atmospheric and functional lamps an agent needs and are based on question QP1 (Section 4.5.3.8). Because no distinction is made in the survey between the number of atmospheric and functional lamps, this information is unavailable. For the purposes of the model, the assumption is made that the ratio of these is always one on one. This gives the following formula for the atmosphere and functional requirements:

$$Atm. \, req = Func. \, req = \left\lfloor \frac{QP1}{2} \right\rfloor$$
4.5.5 Experience update weight

The experience update weight $w$ parameter (Section 3.4.2) will be set at 0.2 and not varied.

4.5.6 Social frequency

The social frequency parameter (Section 3.5.1) will be set at 5 in the default model. If the social frequency is varied, it will be explicitly mentioned.

4.5.7 Assumed Maximum of inter-agent difference

The Assumed Maximum of inter-agent difference will be set at 50 and not varied. This means that if two agents have an average experience difference of 50 percent or higher, their inter-agent difference is said to be 100 percent. This assumption scales linearly, so an actual difference of 25 percent will mean an inter-agent difference of 50 percent.

4.5.8 Monte-Carlo sample size of social satisfaction

The Monte-Carlo sample size will be set at 20 percent and not varied. This means that for a run with 1000 agents, an agent will be compared to 200 randomly chosen peers for the determination of social satisfaction.

4.5.9 Functional lamp satisfaction parameters

The functional lamp satisfaction parameters $a_1, a_2, a_3, a_4$ and $a_5$ (Section 3.6.3) will each be set at 0.276, 0.114, 0.116, 0.214 and 0.280 respectively and not varied. The $a_3$ and $a_4$ parameters, dealing with focus on energy usage for price and environment are treated differently because they scale the same lamp trait: energy efficiency. If these were treated as two separate variables, the energy efficiency would gain an unfair advantage over other traits because it would be counted twice.

These numbers are calculated by taking the average importance of each trait as shown in section “5.6.2” of [2] and scaling these to a number between zero and one. In this calculation, the energy focus and environmental focus are assumed to be two weighted factors of the same characteristic. For clarity on this method, the entire calculation is shown below.
The average Likert scores for colour discrepancy, energy focus, environmental focus, ramp-up time and price are 5.11, 4.22, 4.31, 3.97, 5.20 [2]. We take the average of focus on energy and environmental to calculate relative importance of energy usage: \( \frac{4.22 + 4.31}{2} = 4.265 \). For the four lamp characteristics (colour discrepancy, energy usage, ramp-up time and price) we calculate the weight of each. For colour discrepancy, this weight is \( \frac{5.11}{5.11 + 4.265 + 4.97 + 5.20} \approx 0.276 \). The values for ramp-up time and price are calculated similarly.

For energy usage, the special case, this calculation becomes \( \frac{4.265}{5.11 + 4.265 + 4.97 + 5.20} \approx 0.230 \). This value will be divided among focus on energy and focus on environmental according to their relative importance. The relative importance of focus on energy is \( \frac{4.22}{4.22 + 4.31} \approx 0.495 \) (or 49.5 percent). This means that 0.230 \( \times \) 0.495 \( \approx \) 0.114 of the total weight will be allotted to energy focus and the remainder 0.230 – 0.114 = 0.116 will be used for focus on environment.

Overall, this means the focus for functional lamp satisfaction lies with price and light colour, with energy usage and ramp-up time being of nearly equal importance.

### 4.5.10 Atmospheric lamp satisfaction parameters

The atmospheric lamp satisfaction parameters \( a_1, a_2, a_3, a_4 \) and \( a_5 \) (Section 3.6.3) will each be set at 0.315, 0.112, 0.113, 0.194 and 0.265 respectively and not varied. These numbers are based on [2] and calculated with the same method as explained in the previous section.

This means the main focus for atmospheric lamp satisfaction lies with the light colour, with ramp-up time being the least important.
Chapter 5

Output of the computer model

Having implemented the fully parameterised model, the behaviour of the model can now be studied. In this chapter, the computer implementation of the model is introduced and the tracked variables are shown.

5.1 Introduction

The computer implementation of the model consists of (a) a main screen showing the prevalence of lamps in the model and the characteristics of a selected lamp model and (b) several graphs showing the frequencies of the selection strategies for several cross-sections of the agent population. To explain the information being displayed, several terms need to be introduced.

In the following sections, first the main screen will be introduced, together with a definition for lamp models and lamp tokens. After that, the strategy screens will be introduced.

5.2 The main screen

In this section the main screen of the computer implementation of the model and the measured variables will be introduced and explained. The main screen consists of a graphical user interface which shows a live plot of the predominance of all lamp tokens in the model, as well as offering some means of displaying and changing lamp properties during a run.

An example of the main screen can be seen in Fig. 5.1.
5.2.1 Lamp models and lamp tokens

In Fig. 5.1, the legend is visible in the top left corner and shows all lamp models. As can be seen, there are 19 different lamp models, of which five are of the “LED” type, nine are of the “CFL” type and the remaining five are of the “incandescent” type. These 19 lamp models are abstract prototypes available for the agents to select. A concrete example of a lamp model would be the “Philips CFL Tornado 300lm 5W”: a lamp store may have a lot of bulbs of that lamp model available, but the name itself represents an abstract lamp model.

![Figure 5.1: Main screen of the user interface for the model implementation. Each graph represents one available lamp model. The x-axis shows time (months) and the y-axis shows the total number of lamp tokens per lamp model currently in possession of an agent. The legend shows all available lamp models on the market. The values in the bottom of the screen show the properties of the highlighted lamp model in the legend.](image)

Every agent has an individual need for a number of lamps, some of which performing a functional task an some of which performing an atmospheric task (Section 3.3.2). From the 19 available lamp models, an agent selects individual lamps, or lamp tokens. Every lamp token is an instantiation of one of the 19 lamp models and is in the possession of
an agent. Because the number of lamps an agent requires does not change over time and all broken lamps are replaced immediately, the number of lamp tokens in the model is constant.

To summarise the newly introduced terms:

- A \textit{lamp model} is a prototype of a lamp. The computer simulation has 19 lamp models, listed in the legend of Fig. 5.1.
- A \textit{lamp token} is an instantiation of a lamp model: a concrete light bulb.

### 5.2.2 Main screen

The graphs that can be seen in Fig. 5.1 show the number of lamp tokens currently in the model. Because the sum of all tokens is a constant, the rising of one graph must be compensated by a lowering of one or more other graphs. The running of the model can be controlled in steps of 10, 100 or set to run until further notice.

Each graph can be selected in the legend or by clicking the graph line itself. Doing this fills the input areas in the bottom of the screen with the properties of the selected lamp model. All lamp model properties, apart from the \textit{Type} trait, can be changed during the run. Also it is possible to set the availability of a lamp, taking it from the market or introducing it to the market immediately.

The main screen shows which lamp models are popular and allows manipulation of their traits to see the effects of these changes live.

### 5.3 Strategy selection screens

In Fig. 5.2, the selected strategies of all agents over time is plotted. This strategy selection screen shows the averages. Because we are interested in the choices of “early adopters” and because we suspect anti-conformist agents play a large part in the adoption of new technologies, three separate strategy selection displays have been made for (a) the lowest ten percent, (b) the middle ten percent, and (c) the highest ten percent of all agents when ranked according to the \textit{Social Agreeability} trait (see Section 3.3.2).
Figure 5.2: Graphical output of the model implementation showing the percentile occurrences of each strategy. The legend in the top-left corner shows the strategy labels. The x-axis shows time (months) and the y-axis shows the percentage of strategy selections for every strategy. If the red line, representing “imitation”, indicates 80 percent at some time step, this means that 80 percent of all strategies chosen that time step were “imitation”. The four lines will always add up to 100 percent at any given time step (provided a single strategy selection was made).
Chapter 6

Model validation and revision

Having implemented the fully parameterised model, the behaviour of the model can now be studied. A tipping point analysis will be performed: a study of why the model changes at the points where it does. This is shown to reveal a serious weakness in the lamp satisfaction formula (Section 3.6.3) used in the model and will lead to a change in this formula and a revised model.

6.1 Model settings

The default model will be allowed to run. To ensure stabilisation, the model will be allowed to run 2000 time steps. After it has stabilised, the price of the dominant lamp will be iteratively increased until it has been replaced with a different lamp. The price of the dominant lamp will be raised with €0.10. Then the model will be allowed to stabilise in steps of 100. This process repeats until the popularity of the lamp is overtaken.

6.2 Observations

After the first 2000 steps, the model has stabilised with the €5 LED lamp as most popular with roughly 17000 occurrences. In the remaining text, this lamp will be referred to as “lamp A”. The second most popular lamp, the €6 LED lamp or “lamp B”, has round 1500 occurrences. Strategy selected is relatively stable with repetition at around 77 percent, imitation at around twelve percent, followed by enquiring and optimisation with each around six percent.

Step by step increasing the price of the lamp A shown no change in the model up to €6,40. At €6,50, a tipping point is reached. This can be seen in Fig. 6.1. The
occurrence of lamp A decreases to around 10100, whereas the occurrence of lamp B rises to 9300. During this decrease, a slight drop in the “repetition” strategy is seen, to around 73 percent, in favour of all three others strategies, but notably “imitation”. A new stable point is reached slowly in about 3000 time steps. An graph of the new stable situation can be seen in Fig. 6.2. In this new stable situation, repetition remains lower with around 68 percent, imitation rises to ± 15 percent and enquiring and optimisation also rising to ± eight percent.

![Graph showing the new stable situation](image.png)

**Figure 6.1**: A tipping point in the model when the price of lamp A reaches €6,50. The black vertical line shows the point where in time when the price was increased, the current time being 70 steps after this. Lamp A is highlighted in blue in the legend and the plot. Lamp B is represented by the green line.

Since lamp A is still dominant, the price increase continues. Now after just a single step increase to €6,60, a new tipping point is reached. This is illustrated in Fig. 6.3. During the drop or lamp A, the dominant strategy remains that of repetition at around 65 percent. The “imitation” strategy rises to around 20 percent, with “enquiring” and “optimisation” staying around eight percent. After about 2000 time steps, the new situation has lamp A at around 2000 occurrence and lamp B at around 17000, effectively having replaced each other in popularity. At strategy selection figures do not change and remain roughly the same as during the drop.

### 6.3 Analysis

The initial distribution is likely due to anti-conformist agents not wanting to purchase the most popular LED lamp in the model and settling for the second-best LED lamp which is more expensive but otherwise has similar properties.
Figure 6.2: The new stable situation after a price increase for the most popular lamp, lamp A, highlighted in blue in the legend and the plot. Lamp B is represented by the green line.

Figure 6.3: A new tipping point in the model occurs with the price of lamp A at €6.60. Lamp A (blue) is overtaken by lamp B (green). Again, the black vertical line shows the point where in time when the price was increased, the current time being 70 steps after this.
Chapter 6. Model validation and revision

The price of lamps is used in the model to calculate lamp satisfaction (3.6.3). This lamp satisfaction is used (a) to update the agent’s experience characteristic (3.4.2) and (b) to select the best possible lamp in the “optimisation” and “enquiring” strategies (3.7). Lastly, the experience characteristic is directly used as a measure for subsistence satisfaction (3.6.1) and indirectly as a measure for social satisfaction (3.6.2).

To understand the tipping point of the price change, it is most important to look at the best possible lamp selecting for the “optimisation” and “enquiring” strategies. In these strategies, the best lamp is selected by comparing the satisfaction score of lamps with each other. Each agent values a lamp differently based on its own preferences. When comparing the lamp satisfaction within a single agent however, these preferences are constants and can be removed from the equation.

In fact, an agent has a simple formula for determining the optimal lamp:

\[
Max(\text{Lamp satisfaction}) = \\
Max( \\
a_1(-\text{Colour Discrepancy}) + \\
a_2(\text{Energy Efficiency}) + \\
a_3(\text{Energy Efficiency}) + \\
a_4(-\text{Ramp up Time}) + \\
a_5(-\text{Price}) \\
)
\]

Given that the variables \(a_1\) through \(a_5\) are constants for functional (4.5.9) and atmospheric (4.5.10) lamp satisfaction, we can calculate these scores for lamps A and B:

\[
\text{Functional satisfaction}(\text{Lamp A}) = 0.22(-10) + 0.19(90) + 0.19(90) + 0.17(-2) + 0.23(-50) \\
= 20.16
\]

\[
\text{Functional satisfaction}(\text{Lamp B}) = 0.22(-15) + 0.19(90) + 0.19(90) + 0.17(-1) + 0.23(-60) \\
= 16.93
\]

Note that these values are not the same for every agent in the model and likely none of the agents have these exact numbers as functional lamp satisfaction for the examined lamps,
because the individual agent characteristics are a factor in determining this number. The
difference between these numbers, however, will be the same for all agents because then
the individual traits used in the formula cancel each other out.

The values filled in between the parenthesis are the properties of the respective lamps.
Note that every single increment of the price lowers the functional satisfaction with 0.23
\((a5)\). This means that the price of lamp A needs to be increased with \(\frac{20.16-16.93}{0.23} \approx 14.04\) steps for lamp B to become the preferred functional lamp for all agents. So when
increasing the price with €1,50, lamp B becomes objectively more functionally desirable
than lamp A. This explains the first tipping point in the model when the price of lamp
A reaches €6,50.

The same calculation can be made for atmospheric satisfaction by replacing the values
of \(a1\) through \(a5\):

\[
\text{Atmospheric satisfaction}(\text{Lamp } A) = 0.26(-10) + 0.18(90) + 0.18(90) + 0.16(-2) + 0.22(-50)
\]
\[
= 18.48
\]

\[
\text{Atmospheric satisfaction}(\text{Lamp } B) = 0.26(-15) + 0.18(90) + 0.18(90) + 0.16(-1) + 0.22(-60)
\]
\[
= 15.14
\]

The difference in price now must be \(\frac{18.48-15.14}{0.22} \approx 15.18\) or €1,60 for lamp B to become
objectively the most desirable atmospheric lamp. This explains the second tipping point
in the model when the price of lamp A reaches €6,60.

6.4 Conclusions

This tipping point analysis reveals a weakness in the lamp satisfaction formula: the
chosen implementation for lamp satisfaction leads to objectively more desirable lamps.
In other words: all agents think the same lamp is the best lamp. The only difference is
the extent in which they prefer that lamp. Agents with a high focus for energy efficiency
might subtract a high value from the energy usage value in the satisfaction formula, but
will do so for every lamp in the model.

The behaviour that all agents favour the same lamp - be it with different levels of
satisfaction - clashes with our intuition and the reality: people have different preferences
resulting from their individual characteristics.
The core of the problem is that the differences between lamp satisfaction levels for all agents are equal. To solve this issue it is vital to make these lamp satisfaction differences agent-dependant. A simple correction is to change the lamp satisfaction formula to

\[
Revised\ lamp\ satisfaction = \\
a1 \left( \frac{1}{2} + \frac{100 - Colour\ Flexibility}{100} \right) \times (-Colour\ Discrepancy) + \\
a2 \left( \frac{1}{2} + \frac{Focus\ Energy}{100} \right) \times (Energy\ Efficiency) + \\
a3 \left( \frac{1}{2} + \frac{Focus\ Usage}{100} \right) \times (Energy\ Efficiency) + \\
a4 \times (-Ramp\ up\ Time) + \\
a5 \times (-Price)
\]

By scaling the lamp characteristics by the preferences of the agent (instead of subtracting those values from the total), we ensure that the satisfaction differences between agents will not be equal. As a result of this, agents will have different preferences. The addition of the \( \frac{1}{2} \) to the fraction based on the agent properties ensures that the correction for an agent with exactly the middle point for a property range will be zero. In other words, if an agent’s Colour flexibility is 50 percent, it will have no altered interest in the colour discrepancy. Every point below 50 will decrease the agent’s interest in the lamp characteristic, whereas every point above 50 will increase the agent’s interest in it.

From this point forward, the model with the revised lamp satisfaction formula will be used. Any reference to “the model” will therefore from now on be taken to mean the revised model.
Chapter 7

Model analysis

In the previous chapter, a serious weakness in the lamp satisfaction implementation has been found. Having replaced the lamp satisfaction formula with a new, revised formula, the behaviour of the model can be analysed. In this chapter, the behaviour of the model will be introduced stepwise. Several iterations of the model will be shown while gradually enabling more complex behaviour. This shows the characteristics of the final model and the effects that the design decisions have on the final result.

7.1 A simple model: homo economicus

In the first model iteration, the behaviour of a simple model without social interaction or complex selection strategies will be shown. The resulting model resembles the classical idea of *homo economicus*: a model in which agents behave self-interestedly and rational.

7.1.1 Changes to the full model

The full model has four behavioural strategies that agents can engage in. For this run, all but the “optimisation” strategy have been disabled, making optimising the only available strategy. Also, social interaction has been disabled by setting the *social frequency* parameter (Section 3.5.1) to zero.

7.1.2 Observed behaviour

The observed behaviour can be seen in Fig. 7.1. Only two lamp models have been selected: the €1.5 Incandescent model with roughly 90 percent of all token occurrences and the €5 LED model with the remaining percentage.
In the spirit of completeness, a plot of the overall strategy frequencies has been included in Fig. 7.2.

Running this model for a longer time will not alter the behaviour.

7.1.3 Altering the running model

To observe the behaviour of the *hominens economici* under changing market conditions, a single alteration will be made to the market: the most popular lamp model will be
made unavailable until the model has stabilised and then be made available again.

The behaviour of the model, when the €1.5 Incandescent lamp model is made unavailable at time step 100, can be seen in Fig. 7.3.

![Figure 7.3: Behaviour when €1.5 Incandescent model is made unavailable at time step 100. The highlighted line shows the drop of the unavailable model. The green €5 LED model more than doubles in frequency, but the new winner is the black €2 Incandescent model with 50 percent energy efficiency, claiming roughly two third of the total token frequency.](image)

After the model has stabilised, the unavailable lamp is reintroduced to the market. The change in behaviour after the reintroduction can be seen in Fig. 7.4.

### 7.1.4 Analysis

If the agents have but a single available strategy, there can be no change in the lamp token distribution. This is because the “optimisation” strategy fully depends on the lamp satisfaction formula (Section 6.4), which is unaffected by experience. This means the lamp model frequency plot (Fig. 7.1) will not show any change. We can see the population is split between an inexpensive and inefficient lamp model and a more expensive and energy efficient lamp, with a high preference for the earlier.

Unsurprisingly, in the strategy frequencies plot (Fig. 7.2) we see only a single strategy has been chosen. The drop of the graph to zero in the beginning means that there were one or more time steps in which no agent performed an action. This is to be expected in the first few steps, because actions are only performed when a lamp breaks and every
Figure 7.4: Behaviour when €1.5 Incandescent model is made available again at time step 250. The highlighted line shows the rise of the newly available model. Within 20 time steps, the previously popular black €2 Incandescent model drops to zero. The green €5 LED model slowly loses market share.

agent is provided with new lamps on the first time step, making it unlikely that they break immediately. It is possible for this graph to drop to zero again at random intervals because of the stochastic nature of lamp lifetimes. However, with over 20,000 lamps in the model, this is unlikely to occur.

When the market conditions are changed, we finally see some dynamics. When the agents cannot select their previous first choice, each immediately decides to purchase the second best. The population is split again between purchasing expense and energy efficiency, still with a preference for the initially less expensive lamp but less convincingly.

The strong drop of the blue line in Fig. 7.3 can be explained by the short life time of the €1.5 Incandescent model, averaging only eight months. This means more than 99 percent of the lamp tokens of that model will break within ten time steps. The grow of the other lamp model frequencies is also immediate, because that does not depend on their life time.

Similarly, the slow drop of the green €5 LED model in Fig. 7.4 is due to its long lifetime, averaging 208 months. The quick switch to the newly available lamp model is due to the forced “optimisation” strategy. If the agents had different strategies available, notably “repetition”, the adoption would be much slower and might not happen at all.
7.1.5 Conclusions

Because the main behavioural dynamics of the Consumat model is achieved through the strategy selection mechanism, there is no dynamic behaviour in the *homo economicus* scenario: every agent knows what is best for itself and has no reason to change its selection.

When changes in the market occur, the agents catch on immediately and adapt to the new situation without delay. This is because every time a lamp token breaks, an agent will consider all available options, researching any new developments and pick the very best lamp model available.

7.2 The functional model: repetition and optimisation

In this model iteration, the behaviour of a model without social interaction or social selection strategies will be shown.

7.2.1 Changes to the full model

The full model has four behavioural strategies that agents can engage in. For this run, the functional strategies, “repetition” and “optimisation”, are available while the social strategies are not. Additionally, social interaction remains disabled by setting the *social frequency* parameter (Section 3.5.1) to zero.

7.2.2 Observed behaviour

The observed behaviour can be seen in Fig. 7.5. All lamp models now have some representation in the total lamp tokens selected by the agents. The €1.5 Incandescent lamp model remains most popular, with a little under 50 percent of all total lamp tokens. At a large distance, the second most popular lamp model remains the €5 LED model, which stays under the ten percent total frequency.

A plot of the overall strategy frequencies has been included in Fig. 7.6. The strategy plots of (1) the lowest ten percent social agreeability agents, the “anti-conformist” agents, (2) the middle ten percent, the “average” agents, and (3) the highest ten percent, the “conformist” agents have been included in Fig. 7.7, Fig. 7.8, and Fig. 7.9 respectively.

As before, running this model for a longer time will not alter the lamp model frequencies.
Figure 7.5: The situation after 70 steps with the two functional strategies and no social interaction. The blue, highlighted graph represents the €1.5 Incandescent lamp model, stable at \( \sim 9000 \) lamp tokens. The lower, green graph represents the €5 LED lamp model, stable at \( \sim 1500 \) tokens. All other lamp models lie in the 400-800 token range.

Figure 7.6: The overall average strategy selection overview after 70 steps of the two functional strategies. The top black graph represents the “repetition” strategy. The lower brown graph represents the “optimisation” strategy.

Figure 7.7: The anti-conformist average strategy selection after 70 steps of the two functional strategies. The top black graph represents the “repetition” strategy. The lower brown graph represents the “optimisation” strategy.
7.2.3 Behaviour when removing the most popular model

The most popular lamp model will be made unavailable until a new stable situation arises, after which it will be made available again. To keep the number of images manageable, only plots of the model during the change will be shown. The final stable situations which occur after the change will just be described.

During the change, the behaviour in Fig. 7.10 is observed. The final, stable situation after making the €1,5 Incandescent model unavailable shows the €5 LED model is most popular with $\sim$ 3000 lamp tokens, the €2 Incandescent model with 50 percent energy efficiency a close second with $\sim$ 2500 lamp tokens and all other models stable around the 1000 token mark. Stabilisation takes $\sim$ 300 time steps in total to occur.

The strategy plots for the overall average, the anti-conformist agents, the average agents and the conformist agents have been included in Fig. 7.11, Fig. 7.12, Fig. 7.13, and Fig. 7.14 respectively.

After the model has stabilised, the strategy plots closely resemble the plots as they were before the change (visible in Fig. 7.6, Fig. 7.7, Fig. 7.8, and Fig. 7.9) with the exception of the anti-conformist strategy plot. In the new stable situation, the “repetition” strategy is also dominant for the anti-conformists, with a more than 90 percent selection rate.
7.2.4 Behaviour when reintroducing the lamp model

In this section, the behaviour of the model is shown after reintroducing the previously most popular lamp, the €1,5 Incandescent model.

Fig. 7.15 shows the situation 70 steps after the €1,5 Incandescent model was reintroduced. Fig. 7.16 shows the final, stabilised model. Change is slow to occur and stabilisation takes $\sim 300$ time steps. The final, stable situation shows the previously most popular lamp model as least popular.
Figure 7.13: The average strategies 30 steps after a market change removing the most popular lamp model.

Figure 7.14: The conformist strategies 30 steps after a market change removing the most popular lamp model.

Figure 7.15: The situation 70 steps after the €1.5 Incandescent model was reintroduced. The blue, highlighted and rising graph represents the reintroduced model. The top, green and dropping graph is the €5 LED model. The stable second-highest graph is the €2 Incandescent model which gained popularity after the previous change.

The strategy selection plots during and after the change show significant changes, with one exception which can be seen in Fig. 7.17: the non-conformist agents start optimising much more frequently. The other two agent selections, the average and conformist agents, do not show this behaviour.

7.2.5 Analysis

The most striking difference between the initial situations of homo economicus (Fig. 7.1) and the functional model (Fig. 7.5) is the occurrence of all lamp models in the
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Figure 7.16: The stabilised situation after the €1.5 Incandescent model was reintroduced. The most popular model remains the €2 Incandescent model. The second most popular is the €5 LED model. The previously dominant €1.5 Incandescent model is in the lower half of the “clump” of lines centred around 1000 tokens.

Figure 7.17: The strategy selection of anti-conformist agents 70 steps after the €1.5 Incandescent model was reintroduced. The plot shows a rise in the frequency of optimisation.
latter. This can be explained by the random model initialisation which is done in the first time step. Every agent is assigned a random lamp which breaks immediately, forcing it to perform an action in the very first round. When the only action available was “optimising”, as in the homo economicus model, every agent replaced this initial random lamp with the most suited one available. However, in the functional model, a significant part of the population is content with the lamp model randomly assigned to it, which results in the “repetition” strategy. This explains the model diversity in the functional run.

The only agent cross-section which regularly engages in “optimising” is the anti-conformist group. This can not be explained by the “anti-conformist” label however: the choice between “repetition” and “optimising” has nothing to do with the Social Agreeability trait which was used to produce this label.

When the most popular lamp is removed from the market, the change is again immediate as seen in Fig. 7.10. The large shift in anti-conformist strategy is remarkable, doubly so because the anti-conformist agents get more repetitive when the market changes. Because social strategies in this model run are disabled, this actually means that less choice leads to a higher subsistence (or functional) satisfaction level.

Very significant is the difference we see when reintroducing the previously most popular model. In the homo economicus model, Fig. 7.4, the reintroduction is immediately noticed by all agents and the model regains its former dominance steadily. However, in the functional model, 7.15, the reintroduction is hardly noticed. In Fig. 7.17 we see the anti-conformist agents reacting to this change in the market and adopting the newly available lamp, but the other agents keep turning to the dominant strategy of “repetition” and never even notice the change in the market.

7.2.6 Conclusions

Agents are easily functionally satisfied with their lighting. A significant portion of the population is perfectly happy to receive a random lamp and will keep purchasing that exact model until they are forced to change their behaviour.

The anti-conformist group is always the group initiating and driving change in the model. This can not be explained by the Social Agreeability trait, which in this functional model has no influence. The conclusion must be that from the data on which the agents are based, follows that anti-conformists are not as easily functionally satisfied as more socially agreeable agents. This seems like a fair assumption, but has now been shown by this model.
Lastly, a popular lamp is maintained due to disinterest of the agents. If a popular model is removed from the market and later reintroduced, the agents rarely notice the reintroduction because they have found a satisfactory replacement. Only the anti-conformists notice the new arrival and adopt it. Because there is no social interaction, conformist agents are not confronted with the new products.

7.3 The full model

In this model iteration, the full model will be shown.

7.3.1 Changes to the full model

The full model has all four behavioural strategies that agents can engage in and the default social frequency parameter (Section 3.5.1) of five.

7.3.2 Observed behaviour

7.3.2.1 Initialisation

This section shows the behaviour of the model during the first 70 time steps. In these first 70 time steps we see the €1.50 incandescent lamp starting very high, but quickly dropping while remaining the most popular lamp in the model. This is shown in Fig. 7.18. The second most popular lamp is the €5 LED lamp, which starts out as above average but climbs quickly. All other lamps remain in the lower segments, but none are wholly ignored.

A plot of the overall strategy frequencies has been included in Fig. 7.19. The strategy plots of (1) the lowest ten percent social agreeability agents, the “anti-conformist” agents, (2) the middle ten percent, the “average” agents, and (3) the highest ten percent, the “conformist” agents have been included in Fig. 7.20, Fig. 7.21 and Fig. 7.22 respectively.

A larger difference in strategies can be seen between the selected cross-sections. The anti-conformist agents prefer social strategies, especially imitation and to a lesser extent enquiring, whereas for the other two groups repetition remains dominant. The conformist group prefers imitation as a second best, whereas the average group barely leaves room for any other strategy than repetition.
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Figure 7.18: The situation after 70 steps with the full model. The blue, highlighted graph represents the €1.5 Incandescent lamp model, starting at ~ 8000 lamp tokens but dropping steadily. The lower but rising green graph represents the €5 LED lamp model, starting at ~ 200 tokens. All other lamp models lie near the 500-1000 token range.

Figure 7.19: The overall average strategy selection overview after 70 steps of the full model. “Repetition” quickly becomes the dominant strategy, with “imitation” following at some distance. As time passes, “repetition” becomes more and more prevalent.

Figure 7.20: The anti-conformist average strategy selection after 70 steps of the full model. In this plot, we see the dominance of the social strategies and especially “imitation”. The anti-conformist group is the only group with a significant representation of the “enquiring” strategy.
Figure 7.21: The average average strategy selection overview after 70 steps of the full model. From the start, a clear preference for “repetition” can be seen. While in the first 15 time steps, some average agents engage in imitation, after some time all other strategies dwindle in favour of repetition.

Figure 7.22: The conformist average strategy selection overview after 70 steps of the full model. “Repetition” quickly becomes the dominant strategy, with “imitation” following at some distance. As time passes, “repetition” becomes more and more prevalent.

7.3.2.2 Stabilisation

This section shows the behaviour of the model after stabilisation. When stable, we see the €1,50 incandescent lamp remains the most popular lamp in the model. This is shown in Fig. 7.23. The second most popular lamp remains the €5 LED lamp, with a small difference. The model stabilises slowly and takes ~ 2000 time steps.

The now familiar strategy plots are included as Fig. 7.24, Fig. 7.25, Fig. 7.26, and Fig. 7.27.

7.3.2.3 Popular lamp removal

When taking the most popular lamp out of the market, the model responds by showing an increase in all other lamps on the market. This behaviour can be seen in Fig. 7.28. The strategy change shows a slight drop in repetition in favour of imitation. Only the anti-conformists respond differently, as can be seen in Fig. 7.29.

After the initial change, the model slowly stabilises in ~ 1000 time steps to a new situation as can be seen in Fig. 7.30.
Figure 7.23: The situation after stabilisation in the full model. The blue, highlighted graph represents the €1.5 Incandescent lamp model, stabilising at ~ 6000. The green graph representing the €5 LED lamp model reaches ~ 4000. The next three highest graphs are the €8 LED, the €6 LED and the €10 LED respectively.

Figure 7.24: The overall average strategy selection overview after stabilisation of the full model. “Repetition” remains the dominant strategy, with “imitation” following at a large distance. The other two strategies remain close to zero.

Figure 7.25: The anti-conformist average strategy selection after stabilisation of the full model. “Imitation” remains the most frequently used strategy, but is closely followed by all three other strategies. “Optimisation” is the least frequent, with roughly half the occurrence frequency of “imitation”.
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Figure 7.26: The average average strategy selection overview after 70 steps of the full model. From the start, a clear preference for “repetition” can be seen. While in the first 15 time steps, some average agents engage in imitation, after some time all other strategies dwindle in favour of repetition.

Figure 7.27: The conformist average strategy selection overview after stabilisation of the full model. “Repetition” remains the dominant strategy at $\sim 90$ percent, with “imitation” following at a large distance at $\sim 10$ percent.

Figure 7.28: The first 30 time steps after removing the most popular lamp from the full model. The drop of the €1.5 Incandescent model causes a smaller but equal increase in all other model frequencies.
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Figure 7.29: The anti-conformist strategy response after removing the most popular lamp from the full model. The “optimisation” strategy (highlighted blue graph) drops in favour of imitation and, to a lesser extent, enquiring.

Figure 7.30: The new stable model after removing the most popular lamp from the full model. The €5 LED model remains most popular. A previously uninteresting model, the blue, highlighted €2 Incandescent lamp also gains relatively more in popularity.
### 7.3.2.4 Popular lamp reintroduction

When reintroducing the previously most popular lamp out of the market, the model slowly and finally stabilises after $\sim 1000$ time steps to a new situation, shown in Fig. 7.31. The previously popular lamp never recovers and the currently popular lamp is not much affected by the appearance of a new competitor.

During the reintroduction, no visible change in strategy selection displayed. This can be seen in Fig. 7.32.

![Figure 7.31: The new stable situation after reintroducing the previously removed lamp model, highlighted in blue.](image)

### 7.3.3 Analysis

With the full model dynamics enabled, more complex and gradual changes become apparent. The longer stabilisation period shows a slow but non-monotonic convergence to a stable point. In this, the effects of the social dynamics are visible as they allow agents to directly and indirectly influence each other. The most popular lamp from the previous two runs remains the dominant model, but the second most frequent model does approach it more closely.

The reason for LED lamps as the numbers three, four and five has to do more with life expectancy of those models than with the desire of agents to preserve energy. Sometimes in the social strategies an agent is forced to make a (partially) random pick from the lamps available on the market. Random picks of longer lasting models affect the model more, because these lamps are longer in possession of the agents before being replaced.
Interesting to see remains the difference between the anti-conformist group and the other two groups, with the first generally focussing more on social strategies and the latter more on the “repetition” strategy. This difference is visible in stable situations, but also when the market changes, as the anti-conformist group keeps showing the largest changes in strategy selection.

The model behaviour on removal of a prominent lamp shows an immediate and equal increase in all other lamp models. Again, this shows agents are easily satisfied with their lighting, as any random replacement will mostly do. After some time, we see one or two lamp models gain relatively more than the others, indicating the more critical agents are switching over to models more suited to their needs.

The reintroduction of a previously popular lamp model shows that it is very difficult for even a good lamp model to achieve popularity from a disadvantage. While adopted by the anti-conformist agents, the new lamp never gains enough popularity to be selected for its social criteria. Because most agents are not especially interested in functional criteria either, this presents the new lamp model with too high a barrier to break through.

### 7.3.4 Conclusions

With the inclusion of social strategies, more complex behaviour emerges. The same underlying principles as seen in the previous models remain, however. Agents are easily
satisfied with any lamp model and are unwilling to spend time and energy on improving a situation they perceive as “good enough”. The notable exceptions are the anti-conformist agents, which adopt changes earliest and are sensitise to social developments. This behaviour shows anti-conformist agents are keenly aware of social developments and adjust their choices accordingly.

Because these anti-conformists are such a small group (∼ 10 percent), their choices do not change the social landscape enough to trigger other agents into following them. For the anti-conformists this must seem like a relief, because this means their choices are not picked up by main-stream consumers.

This also shows the problem a new lamp model is faced with: the only people interested in light innovation, the anti-conformists, do not have enough numbers to convert other agents to adopters of new technology. This means that the majority of consumers can not be easily reached because they are not interested in improving on their current situation and not interested in what a minatory group does. This results in no way to gain a foothold in these agent’s households.

The only market change that will trigger a reaction from the average agent, is a change in the product they are used to buying. The average agent is only willing to change habits if their normal lamp model somehow becomes unavailable, much more expensive or otherwise changes so that it no longer suits their needs.
Chapter 8

Realistic simulation

In the previous chapter, the behaviour of the model has been shown in several example situations. However, these situations (such as a particular lamp type disappearing from the market completely, only to later reappear) are not particularly realistic and were contrived to demonstrate the behaviour of the model. In this chapter, we will examine a more realistic scenario using the model.

8.1 Simulation scenario

The model will be used to examine the consumer behaviour for the 2000-2020 lighting market situation in the Netherlands. The most notable events during this period are the introduction of LED lamps onto the consumer market and the “ban on bulbs”, gradually phasing out incandescent lamps. Below, the time line for the scenario is presented, together with how the events in the lighting market will be simulated in our model. In this section, some assumptions are made and clearly indicated as such.

8.1.1 Models used

Similar to Chapter 7, we will run the experiments using three versions of the model:

- the *homo economicus* version, without social interaction and with only the “optimisation” strategy available;
- the functional version, without social interaction and without the social strategies available;
- the full model.
8.1.2 Time line resources

The time line presented here is based on informal research using freely available information. Not all events and sources are expected to be completely accurate, however we assume they give a good indication of the time line of events in the consumer lighting market. Sources are included as a reference. Because some of these sources refer to the American lighting market, the assumption is made that the European market resembles the US market.

8.1.3 LED lighting development

In 2000, LED lighting was not generally available to the consumer and did not have any market penetration\(^1\). From several online sources\(^2\), we learn that LED lighting became commercially viable for consumers around the year 2009. Before that time, LED lamps powerful enough to replace the normal lamps used in households were available, but for high prices and with a lower energy efficiency.

In 2007, the average price of a LED lamp in the Netherlands was €25, with an expected decrease in price of 10 percent per year\(^3\). In the years before, the prices of consumer LED lighting had already dropped, meaning that LED lighting became an option (albeit an expensive option) for the average consumer. In the model, we assume that the introduction of LED lighting to the consumer market occurred in 2005 with high prices, averaging over €40. Before this time, LED lighting may have been available to a determined consumer, but not as a regular option.

Based on historical LED energy efficiency data\(^4\), the development of energy efficiency has been estimated from 2005 to 2020.

8.1.4 Other market developments

It is reasonable to assume other types of lighting have also undergone changes in the period from 2000 to 2020. However, with one exception, these changes will be ignored. The only other mutation that we assume in the market data is a slight increase in price for incandescent lighting starting in 2012, the year incandescent light bulbs were restricted in the EU.


\(^3\) [http://www.duurzaamthuis.nl/gloeilamp-spaarlamp-of-led-lamp](http://www.duurzaamthuis.nl/gloeilamp-spaarlamp-of-led-lamp), Dutch

8.1.5 Price and efficiency determination

The availability, prices and efficiencies of LED lighting will be varied throughout the model run, as well as the prices of incandescent lighting. The following formulae are used to determine the various aspects.

8.1.5.1 LED lamp availability

\[
LED\ available = \begin{cases} 
no & \text{if year} \leq 2005 \\
yes & \text{otherwise}
\end{cases}
\]

8.1.5.2 LED lamp price

The benchmark price for LED lighting are the prices in 2014, the data research performed for this thesis. These benchmark prices will be indicated by \( P \).

For the period from 2014 onwards, we assume a price decrease of five percent per year, giving this formula:

\[
Price = 0.95^{year-2014} P
\]

For the 2007 to 2013 time period, we estimate a ten percent yearly increase. This means that the further back we go, the more expensive LED lamps become. We implement this by increasing the price by ten percent for every previous year starting at 2014. This results in the following formula:

\[
Price = 1.10^{2014-\text{year}} P
\]

For the initial two years after introduction, 2005 and 2006, we assume a significantly higher price of factors 5\( P \) and 2.5\( P \) respectively:

\[
Price = P \times (2007 - \text{year}) \times 2.5
\]

8.1.5.3 LED lamp efficiency

The benchmark efficiency for LED lighting is again the measurement of 2014. This benchmark efficiency will be indicated by \( E \). Before 2014, we estimate a five percent
increase in efficiency per year. This means that the further back we go, the less efficient LED lamps become. Again we implement this decreasing the price by five percent for every previous year starting at 2014. After 2014, we assume a one percent increase per year.

\[
\text{LED efficiency} = \begin{cases} 
0.95^{2014-\text{year}} E & \text{if } \text{year} \leq 2014 \\
1.01^{\text{year}-2014} E & \text{otherwise}
\end{cases}
\]

8.1.5.4 Incandescent lamp prices

As with the other values, the benchmark prices for incandescent lamps will be those in 2014 and denoted by \(P\). Up to 2011, the prices are assumed to be stable and are the same as in 2012. From 2012 to 2014, we assume a five percent increase in price per year. After 2014, we assume a two percent increase in price per year.

\[
\text{Incandescent price} = \begin{cases} 
0.95^{2014-\text{year}} E & \text{if } 2012 \leq \text{year} \leq 2014 \\
1.02^{\text{year}-2014} E & \text{if } \text{year} \leq 2014
\end{cases}
\]

8.1.6 Implementation

The yearly changes are not implemented as a gradual change but instead take effect at the beginning of a new year.

8.2 Homo economicus

The first model version to be tested is the most basic variant. We will look at the initial situation in the year 2000, the subsequent developments and the final situation in 2020.

8.2.1 Model overview

As in Chapter 7, the homo economicus model version has all but the “optimisation” strategy disabled, making optimising the only available strategy. Also, social interaction has been disabled by setting the social frequency parameter (Section 3.5.1) to zero.
8.2.2 Initial situation in 2000

All lamp tokens in the model are of the least expensive incandescent type. The strategy selection will not be discussed, because only a single strategy is available.

8.2.3 Developments

The first change in the lamp selection of the homo economicus agents can be seen in 2014, when the least expensive LED lamp becomes a viable option for a selection of agents. This can be seen in Figure 8.1. The less-than-smooth pattern is due to a quirk of the implementation: all changes in the market for a year are effected at the beginning of that year.

![Figure 8.1: The lamp token distribution of homo economicus agents in 2017. The yearly jumping pattern can be explained by the market change process: at the beginning of each year, the prices and efficiencies of the lamp models are updated. In the first nine to ten months of each year, we see a rise in the highlighted lamp model because the average life expectancy of the abandoned lamp type is eight months.](image)

8.2.4 Final situation in 2020

In 2020, the LED lamp has overtaken the incandescent lamp in terms of numbers, as can be seen in Figure 8.2. In 2018 the LED lamp becomes more prevalent in the homes of consumers, meaning effectively that in 2018 it is the best possible lamp for a large number\(^5\) of agents.

\(^5\)We cannot say “for a majority” of agents, because agents have different numbers of lamps in use.
8.2.5 Discussion of results

For all agents, incandescent lighting remains the best possible choice up to 2014. Only at this point in time is the price difference between incandescent lamps and LED lighting small enough for agents to consider switching to the much more efficient LED lighting.

Due to the market development of LED lamps becoming less pricey and more efficient, LED lamps gain in popularity from then on. This process is expedited by incandescent lamps becoming slightly more expensive, although the nature of homo economicus mitigates the effects of this development due to their tendency to investigate all market options. The sharper change in the graphs at the beginning of each simulated year are the result of the discrete jumps we introduced in the market data, by which new prices and efficiencies go into effect at the start of each new year.

An interesting point to note is that the year this is being written, 2014, is that the first year that some agents choose LED lighting. Before this point, the agents in the model do not consider LED lighting to be a viable alternative to incandescent lighting.

8.3 Functional model

The second model version to be tested is the functional variant. Again, we will look at the initial situation in the year 2000, the subsequent developments and the final situation in 2020.
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8.3.1 Model overview

As in Chapter 7, for this run the functional strategies, “repetition” and “optimisation”, are available while the social strategies are not. Additionally, social interaction remains disabled by setting the social frequency parameter (Section 3.5.1) to zero.

8.3.2 Initial situation in 2000

The initial situation in 2000 shows the most popular lamp to be the least expensive incandescent bulb. All other lamp models remain roughly equal with a low frequency, as seen in Figure 8.3. This spread is again due to the interplay of the random initialisation of the model and the “repetition” strategy: a selection of the agents is simply content with the random lamp model assigned and keeps that.

![Figure 8.3: The lamp token distribution of the functional model in 2020.](image)

The strategy selection shows a high preference for the “repetition” strategy, as can be seen in Figure 8.4. The anti-conformist agents are the only group in the model to have a significant representation in the “optimisation” strategy, as can be seen in Figure 8.5.

8.3.3 Developments

The first notable change in lamp frequency plots can be seen in 2016, as shown in Figure 8.6. It is not unexpected that we see change occur later than in the homo economicus model version, because agents here have the “repetition” strategy available. As before, we see that this is the dominant strategy as shown in Figures 8.7 and 8.8.
Figure 8.4: The overall strategy selection overview in 2000 of the two functional strategies. The top graph shows the dominant “repetition” strategy.

Figure 8.5: The anti-conformist strategies in 2000, showing the two functional strategies. The highlighted strategy shows the “optimisation” strategy.

Figure 8.6: The lamp token distribution of the functional model in 2018, showing the change starting in 2016.

Especially the change in strategy for the anti-conformist agents (Figure 8.8) is interesting, because it shows that the introduction of a viable new lamp is noticed soonest by anti-conformist agents. After these have switched to the new and better lamp type, they find that this lamp indeed fits their requirements and fall back to the “repetition” strategy.
8.3.4 Final situation in 2020

After the changes in 2016, the model output does not change again. The final situation can be seen in Figure 8.9. The strategy selection also does not undergo any further change and remains as has been seen in Figure 8.7.

In 2020, the model shows not even ten percent frequency for LED lighting. From the *homo economicus* experiment, we know that LED lighting at this point in time is the best option for the majority of lamp slots in the model. Due to being generally satisfied and defaulting to the “repetition” strategy, most agents do not realise this. Interestingly, we can see here that the effects of the “ban on bulbs” have no great impact on the strategy selection of the majority of agents: most are happy to pay slightly more for their usual bulb. Only a more drastic measure could force them to change customs.

8.3.5 Discussion of results

Mimicking the results of this model version in Chapter 7, change is slow. The agents in the model are generally satisfied with their lighting and have no motivation to invest time and energy in possible improvement. The agents that switch earliest are the anti-conformist agents, however, as has been noted before in Chapter 7.2.5, this is not due to their anti-conformist tendencies (but instead it has been suggested in Chapter 7.2.6 that a likely conclusion is that anti-conformist agents are not as easily functionally satisfied as more socially agreeable agents).
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Figure 8.9: The final lamp token distribution of the functional model in 2020.

The prediction made by the model, less than ten percent frequency for LED lighting, seems very conservative. Informal estimates give a market penetration of 30 to 50 percent to LED lighting in the Dutch consumer market in 2014. The exact sources of these claims are unknown, as is the used definition for “market penetration”. At this time there are no sources available to make any reliable comparison.

8.4 Full model

The final model version to be tested is the full model. Similarly as before, we will look at the initial situation in the year 2000, the subsequent developments and the final situation in 2020.

8.4.1 Model overview

The full model is used. To compare our simulation results more easily with market research, as an additional measurement we will also keep track of the percentage of agents which have at least one LED lamp in use. These results will be presented with the final situation in 2020.
### 8.4.2 Initial situation in 2000

The initial situation in 2000 shows the most popular lamp to be the least expensive incandescent bulb. All other lamp models again remain roughly equal with a low frequency, as seen in Figure 8.10.

![Figure 8.10: The initial lamp token distribution of the full model in 2000.](image)

As with the functional model before, the strategy selection shows a high preference for the “repetition” strategy, as can be seen in Figure 8.11. Again, the anti-conformist agents are the only group in the model to behave differently, favouring the social strategies as shown in Figure 8.12.

![Figure 8.11: The overall strategy selection overview in 2000 of the full strategy set. The top graph shows the dominant “repetition” strategy.](image)

![Figure 8.12: The anti-conformist strategies in 2000 of the full strategy set. This group is the only one to differ from the overall strategy selection.](image)
8.4.3 Developments

Development in the model is slow. Starting after the LED lamp introduction in 2005, we see an immediate but very gradual appearance of the LED lamps, as shown in Figure 8.13. No notable change in strategies for any group accompanies it.

![Figure 8.13: The lamp token distribution of the full model in 2007, after the introduction of LED lamps to the market in 2005.](image)

This slow rise continues as can be seen in Figure 8.14 showing the developments until 2015. We see a more rapid increase beginning in 2014, which is the same year the *hominis economici* started purchasing LED lighting. Especially noteworthy is that the frequency of the most popular incandescent lamp does not appear to drop and remains steady.

Also in 2014 we see a slight rise of the “repetition” strategy in the overall graph, shown in Figure 8.15. This can be explained by behaviour changes in the anti-conformist group as shown in Figure 8.16. Here it can be seen that the previously dominant “enquiring” strategy drops in favour of all three remaining strategies, but most notably “optimisation”. The overall averaged effects of these major strategy shifts in the anti-conformist group are however slim.

8.4.4 Final situation in 2020

The gradual change seen in the development of the model continues without alteration. The situation in 2020 can be seen in Figure 8.17. The second most frequent lamp in the model now is the least expensive LED lamp. The frequency of the top incandescent
Figure 8.14: The lamp token distribution of the full model in 2015.

Figure 8.15: The overall strategy selection overview in 2015 of the full strategy set. The top graph shows the dominant “repetition” strategy.

Figure 8.16: The anti-conformist strategies in 2015 of the full strategy set, showing the drop of the previously dominant “enquiring” strategy.

The lamp remains just above 7000, which is the same as at the beginning of the simulation (see Figure 8.10). This shows that, while the LED lamp is being adopted by agents interested in energy efficiency, the agents less motivated by energy efficiency remain content with their choice.

The final strategy selection plots show no remarkable change over the initial average situation (Figure 8.11) with a slightly higher repetition rate than the initial situation, as shown in Figure 8.18. The only group with a significant strategy change is the anti-conformist group in Figure 8.19, where “imitation” has become the dominant strategy at the expense of “enquiring”.

Figure 8.17: The lamp token distribution of the full model in 2020. Dominant remains the least expensive incandescent lamp. Second most popular in 2020 is the least expensive LED lamp, represented by the green line.

For better comparison to other data sources, the percentage of agents which have at least one LED lamp in their possession has also been measured at the beginning of each year. In 2005 at the moment of LED lamp introduction, this figure was predictably 0 percent. Come 2006, just over 10 percent of the agents had purchased at least one LED lamp. In 2013, this number had risen to 20 percent. In 2014 this number had linearly risen to 21 percent. At the end of the year 2020, exactly 24 percent of all agents had at least one LED lamp in use.

Figure 8.18: The overall strategy selection overview in 2020 of the full strategy set at the end of the simulation.

Figure 8.19: The anti-conformist strategies in 2020 of the full strategy set at the end of the simulation.
8.4.5 Discussion of results

Probably the most interesting outcome of this simulation is the lack of change in the number of incandescent bulbs in the model. At the end of the simulation in 2020, there are roughly 6 cheap incandescent bulbs for every inexpensive LED lamp in agent’s homes. The introduction of the LED lamp and the gradual price increase of the incandescent lamps appears not to have affected the buyers of those latter lamps at all. Again this confirms that the agents in our model are quickly satisfied with their lamp choice and require drastic outside involvement to invest time and effort into re-evaluation.

As in all simulations before, the largest changes in strategy selection came from the anti-conformist group. The initial predominance of the “enquiring” strategy is unsurprising, because from previous experiments we have seen that this group is not easily functionally satisfied and social strategies come natural to this group. The change to “imitation” shows that this group reaches a higher level of functional satisfaction during the model run, which again is unsurprising because a better lamp\(^6\) is available to them at the end of the simulation in 2020.

\(^6\)“Better” as determined by the agents themselves as shown in the *homo economicus* simulation.
Chapter 9

Discussion and conclusions

In this chapter, the discussion of the results and the conclusions of this thesis will be presented. The research questions from Chapter 1 will be answered in detail.

9.1 Research questions

For ease of reading, the research questions from Chapter 1.2 are repeated here.

9.1.1 Implementation-specific research questions

(I) How can we implement a multi-agent system to aid the analysis of the lighting market based on the Consumat II model?

(I.a) How can we best represent our domain-specific knowledge for efficient use by the model?

(I.b) How can we best formalise the behaviour of the model for computational efficiency?

(I.c) How can we best identify which consumer characteristics are sufficient and suited to model our chosen field?

(I.d) How can we best model social influence for the agents in the Consumat II model for our model?

(I.e) Is Consumat II sufficient to model the lighting market and consumers as found in a previous market analysis [2]?

(I.f) How can we improve the Consumat II model for future research?
9.1.2 Domain-specific research questions

(II) How can we facilitate adoption of energy-efficient technologies in the lighting market?

(II.a) Where are the stable points (i.e. the possible final states) in the model and which variables affect these in what way?

(II.b) How does the social model affect the diffusion of new technologies?

9.2 The implementation-specific research questions

To answer the first main question of this thesis, *how can we implement a multi-agent system to aid the analysis of the lighting market based on the Consumat II model*, first we will answer the sub-questions I.a-I.f to later return to the main question.

9.2.1 I.a: domain-specific knowledge

(I.a) How can we best represent our domain-specific knowledge for efficient use by the model?

The domain-specific knowledge in the model takes two distinct forms: (1) the knowledge incorporated into the model and (2) the knowledge for the model to work with. An example of the first sort is the lamp satisfaction formula (Chapter 3.6.3), which is used in the model to determine how satisfied an agent will be with a particular lamp. This is highly domain-specific and requires knowledge of the lamp market and consumers to formulate. If we want to apply this model to a different market, a new satisfaction formula will need to be created. An example of the latter sort of information is the lamp types and their characteristics (such as price, efficiency, etc). This information is used to create the artificial market in which the agents operate.

The first type of knowledge is the data incorporated into the model. This knowledge has also been incorporated into the source code of the model implementation. This has the advantage of allowing for extremely fast running of the model. This speed is important, because the domain-specific knowledge is very important in the logic of the model. Our chosen example, the lamp satisfaction formula, will be called several hundred times in each time step. It is possible to include this model knowledge into the model itself because it is static: during a run, the lamp satisfaction formula does not change. The disadvantages of this approach are twofold, one practical and one theoretical. Firstly,
including domain knowledge in the source code does not allow change to the model itself while it is running: any changes to the model require it to be shut down and recompiled. Secondly, a clear distinction between model and domain-specific knowledge is preferred, because this allows for cleaner changes to the model and ease of re-use for other domains.

The second problem, separation between model and knowledge, has been ameliorated by using modern programming techniques. The implementation of the general model has been contained in one section of the source code, whereas all the extra information needed to create the lighting-specific model is kept in a separate section. In jargon, the general model has been implemented as an abstract base class and the lighting-specific model as a subclass. More of these subclasses can be created for different domains, while retaining the common base class model.

The second type of knowledge in the model is the domain-specific data that the model has to work with and manipulate. This consists of the agents with their properties and the lamp types with their properties. The initial data is supplied to the model using plain-text files and is processed during model initialisation. During a run, it is possible to reload this data from a different source. This feature has, for example, been used to manipulate the market in Chapter 7 and to simulate the changing market situations in Chapter 8. The plain-text files can easily be read and changed by people unfamiliar with the specific model or with programming in general.

To summarise, the three considerations for inclusion of domain-specific knowledge have been (1) running speed, (2) separation between model and domain, and (3) ease of modification/application to a new domain. For dynamic data, data which is known to change during the run of the model, the most dynamic solution has been used by loading this from external and easily edited files, completely separate from the model implementation. For static data, the knowledge has been incorporated in an isolated section of the model source code.

In answer to question I.a, of how to represent our domain-specific knowledge for efficient use by the model, we can say that two types of efficiency have been considered: run-time efficiency and efficiency of change/re-use. Data which is dynamic in nature and parameters which need to be changed often, must be external to the model itself. In an ideal situation, static domain-specific knowledge would be external to the model also. In favour of run-time efficiency the decision has been made to use programming techniques to achieve this separation in the source code of the model implementation instead. This choice has preserved the separation between the model and the domain, but does not allow for modification by non-programmers.
For the research, I feel the correct balance has been found. Once the model was designed, little change was needed to the source code of the model. During the different simulations, extensive changes have been made to the input files and the dynamic data during model runs. The running speed of the model is sufficient and the choice to include static data into the model has proven not to be too large a hurdle to comfortably take during experimentation.

**9.2.2 I.b: computational efficiency**

(I.b) How can we best formalise the behaviour of the model for computational efficiency?

For the model implementation, two kinds of computational efficiency have been considered: time complexity and space complexity. While designing a computer simulation, thought must be given to the run-time speed of the simulation. Basic operations must be as simple as possible and necessary complexity must be efficiently encoded. Also the memory footprint of the program must be considered. We would like to run a multi-agent simulation with unique and dynamic agents, which means that traits for every single one must be stored in computer memory during the run of the simulation.

To answer question I.b, first we will discuss the relevant implementation choices.

By implementing the model using a programming language which compiles to native machine code, the largest possible potential speed has been secured. The basic Consumat II decision process is not computationally complex; complexity results from the specific implementations of agent strategies and social interaction. This can for instance be seen in the “enquiring” strategy (Chapter 3.7), which is one of the more demanding strategies because it requires (a) selecting a random peer, (b) requesting all the lamps in their possession, (c) sometimes comparing to all lamp types in the model, and (d) calculating the expected satisfaction of each.

It is important that these basic operations can be performed with speed and efficiency, because they are executed extensively during a single time step. As we have seen in the previous section 9.2.1, the representation of domain-specific knowledge in the model has been partially dictated by runtime speed considerations. Basic operations which involve domain-specific knowledge, such as the lamp satisfaction function, have been designed based on the domain information but kept artificially simple, as must be done in model development. By keeping the basic operations simple, the computer implementation of these can be done efficiently and without mistakes.

One area where the initial implementation failed in regards to speed is the determination of similarity to other agents (Chapter 3.6.2). Currently this is implemented by choosing a
random selection of the total population to compare to. Ideally we would like to compare the current agent to all other agents in the model, but this proved too computationally expensive. In this case, sampling the total population is a valid and defensible solution.

Up to this point we have spoken only of runtime speed efficiency. To ensure efficient use of computer memory, the exact data which needed to be stored for every agent has been identified early in the design process. This can be seen in Chapter 3.2.1 for the lamp properties and Chapter 3.3.2 for the agent properties. Note that the type of data (e.g. “integer”) and the type of information (e.g. “percent”) is included in the table. Most of these values can be encoded in an eight-bit (or one byte) variable, which can hold values from 0 to 255 and is the smallest useful\footnote{Smaller units than a byte can be utilised, but because modern computers are most often designed to work with eight-bit chunks of data, this comes with a generally unacceptable performance overhead and complexity.} unit available to store information in a computer. The translation to computer implementation with minimal memory usage has been facilitated by focussing on types of data and storage size from the beginning of the design process.

So in answer to question \textit{I.b}, we can say that the current model has been made computationally efficient for both runtime speed and memory usage by being aware of both requirements during the design process. More concretely, this means keeping track of variable ranges of data and the time complexity of frequent operations during design. No design decisions have been based on efficiency, however, until the initial solution was shown to be insufficient (such was the case for the determination of similarity to other agents as discussed above). Keeping track of the information needed to determine computational efficiency has led to a clear model implementation and a simple means of changing the implementation in the right places once the initial solution was proven to be insufficient.

9.2.3 \textbf{I.c: consumer characteristics}

(I.c) How can we best identify which consumer characteristics are sufficient and suited to model our chosen field?

The selected consumer characteristics can be found in Chapter 3.3.2 and repeated here: \textit{subsistence flexibility; colour flexibility; energy focus; usage focus; social flexibility; social agreeability; experience; atmosphere requirements; and functional requirements.}

Two of these traits are directly connected to the Consumat II model: \textit{subsistence flexibility} and \textit{social flexibility}. The social trait is an adaptation of the “uncertainty” axis of
the Consumat, as explained in Chapter 2.2.3. These two agent characteristics represent the thresholds for behaviour selection in the Consumat II strategy selection process and are (in some form) mandatory for the Consumat model.

One trait relates to the social model used in this simulation: social agreeability. The other characteristics are based directly on domain-specific requirements of the agents: colour flexibility, energy focus and usage focus for the lamp qualities an agent prefers; experience for the opinion an agent has of different types of lighting; and atmosphere requirements and functional requirements to denote how many lamps an agent needs. During the design phase of the model, income was also considered as a consumer trait, but dropped because its precise influence on lamp purchasing considerations is unknown and our reference study (Chapter 5.9.5 of [2]) found no significant effects of income in the purchasing behaviour.

The domain-specific characteristics were pre-selected based on the data obtained from the questionnaire by [2], extended out of necessity and pruned during the model design phase. The experience characteristic – vital to the model because it equals an agent’s functional satisfaction for different lamp types – in particular is an odd duck, being no more than a weighted running average of the lamp satisfaction formula. The atmosphere requirements and functional requirements, storing how many lamps an agent has need for, are not very interesting characteristics in the model but also needed for a complete simulation. The colour flexibility, energy focus and usage focus traits are included because these we consider these to be the most interesting and prominent lamp characteristics for which consumers have a strong preference. For other lamp characteristics, such as price and ramp-up time, we assumed a non-significant difference between agents in preference. This ranking of “prominent” and “not significant” was reached by discussion and interpretation of collected data, but ultimately comes down to an assumption. I think that the results of the simulation have shown our chosen characteristics to be reasonable and suitable, but no analysis of inclusion or exclusion of certain traits has been done during this thesis.

Based on the thesis, one possible way to answer question I.c is to summarise how it was done for our model. A small number of consumer characteristics are pre-supposed by the Consumat model. A candidate list of possibly relevant domain-specific consumer characteristics has been suggested by previous research. An assumption has been made about the most prominent consumer characteristics and the lighting simulation has been designed around those. To determine whether the chosen characteristics were actually most suited for the simulation, different models would need to be created and their behaviour studied.
9.2.4 I.d: social influence

(I.d) How can we best model social influence for the agents in the Consumat II model for our model?

Social influence can be found in two places in the model. The first and most obvious is the stochastic social encounters agents have, which is described in Chapter 3.5.2. The second works through the social strategies of the behaviour selection process, described in Chapter 3.7.

The update of agent’s opinions based on social encounters have by design been kept simple. Once a randomly decided contact takes place, a peer is selected with a preference for similar agents. An experience update takes place by shifting the experience characteristic slightly towards or away from that peer. This is a minimal model with two complications: the first is the assumption that an agents is more likely to encounter similar agents and the second is that the response of anti-conformist agents to social interaction will be different from their more conformist counterparts. We feel these are reasonable assumptions, but have been hesitant to complicate the social interaction further, because this would require additional assumptions based on very little data. To my knowledge, no studies have been done towards the effects of social interaction in the lighting market. Without this specific data, any further deviation from the basic “update” model would be speculative.

The effects of the social strategies, “imitation” and “enquiring”, are limited to lamp selection and do not directly influence the experience of agents. The behavioural implications of these strategies are for the most part dictated by the Consumat model, but some freedom exists in choosing the specific implementations. Again, a large consideration in defining the social behaviours has been the assumption that anti-conformist agents behave differently from conformist agents in social strategies. Also the similarity bias for social interaction has been included. No further complications have been added to the “default” interpretation of the Consumat strategies.

In answer to question I.d, we can say the most basic models for social interaction for both social encounters and the social strategies have been reservedly modified to include evidence-based assumptions. Because social interaction and especially social strategies are a key point in the Consumat model, the implementation of both strongly affects the behaviour of the model. With the chosen implementations, I am confident that we have stayed close to the intended behaviour of the social strategies and have not introduced artificial constraints.
9.2.5  I.e: modelling the lighting market

(I.e) Is Consumat II sufficient to model the lighting market and consumers as found in a previous market analysis [2]?

We can interpret and answer this question in a number of different ways, two of which will be considered here. The first interpretation is whether the model is sufficiently complex to be able to incorporate all relevant market data as found in Kattenwinkel’s study. The second interpretation is whether the model has produced results similar to those found in Kattenwinkel’s market analysis.

The market analysis has been used as a means to select relevant characteristics for inclusion in the model during the design phase. Some characteristics have been dropped in favour of simplicity and lack of research (see Chapter 9.2.3), but we have been able to include the selected traits cleanly into the model. Further inclusions or changes are in no way limited by the model itself. The two dimensions used for the behaviour selection mechanism in this model, functional satisfaction and social satisfaction, resulted in satisfactory behaviour and intuitively correct simulation responses to real-world market changes. Because of this, I argue that the Consumat II model created for the lighting market is sufficiently complex to meaningfully include the consumer characteristics found in the reference study.

As noted in Chapters 8.3.5 and 8.4.5, the rise of the LED lamps in the model is slow and likely does not accurately reflect the real market developments of the last decade or so. In the 2012 reference study, roughly half of the respondents indicated having already purchased at least one LED lamp. In our realistic full model simulation, the results show roughly six percent of all lamp tokens in the model in 2012 to be LED lamps (Figure 8.14). As discussed in Chapter 8.4.4, in 2012 roughly 20 percent of the simulated agents had at least one LED lamp in their possession. This slower progression is consistent with earlier comparisons to real market data and shows a delayed rise in LED lamps in the model. Reasons and possible solutions for this will be discussed in the next section 9.2.6.

However, when looking at the implications of the simulation results, we find a strong resemblance with the reference study. In Chapter 6.2 of Kattenwinkel’s thesis, three possible explanations are proposed for the low correlations found in the study. From this section, we quote the third and most likely reason:

“The third reason would be that consumers just do not care much about lamp types. Involvement could just be too low for the suggested variables
Chapter 9. Discussion and conclusions

This hypothesis is supported by the focus group, as well as the following outcomes: [...] The overall impression talking to people in-depth about the subject, as well as talking to industry experts and the focus group supports the suggestion of low involvement.

This same conclusion can be reached by reviewing the simulation results, as we have done in Chapter 8.4.5:

“Again this confirms that the agents in our model are quickly satisfied with their lamp choice and require drastic outside involvement to invest time and effort into re-evaluation.”

Based on this result, I am confident in claiming that the current model is sufficient to capture the trends in the lighting market and its development under changing circumstances, even though it likely does not reflect the magnitude of the developments.

9.2.6 I.f: improving the model

(I.f) How can we improve the Consumat II model for future research?

Several quirks of the implementation have been mentioned in previous chapters and are repeated here:

• Agents will replace a lamp immediately after breaking and will not buy in bulk.
• At the start of the simulation, agents are initialised with random lamps in their possession which need replacing immediately.
• The realistic data is loaded into the model once annually, providing no gradual changes during a year.

These points could be better implemented given more time and have been left unchanged because their impact was deemed low enough not to be a significant factor.

Missing or unavailable data has also led to a number of assumptions:

• Initial experience with different types of lighting has been randomly assigned.
• Missing data for the number of atmospheric and functional lamps per household led to the assumption both are equally represented.

• Information for social influence in the lighting market is wholly missing, making the Social Frequency parameter (Chapter 4.5.6) a shot in the dark.

• Agent characteristics are sometimes based on relevant but not completely accurate question-answer pairs. A notable example is the social agreeability trait (Chapter 4.5.4.6).

• The price and efficiency changes of lamps in the realistic simulation data has been estimated based on informal sources and is incomplete.

Some of the missing data is currently – as far as we know – non-existent and thus some estimations are necessary at this point in time. In other cases not enough time was available to gather the data properly. For example in the case of the historical lamp data, a separate thesis could be written about past developments, changes and trends. Each of these points could be improved upon by gathering more information.

All the items above have been discussed in the relevant sections of the thesis before. We will now consider three not-yet-discussed and more fundamental concerns about the model. The first concerns a missing but possibly important lamp characteristic in the lamp satisfaction calculation. The second concerns the implementation of social agreeability and the “anti-conformists”. Lastly we consider an important form of external influence that has not yet been discussed.

In the lamp satisfaction calculation (Chapter 6.4), five factors are included: light colour, energy efficiency relating to cost, energy efficiency relating to environment, ramp-up time, and price. Absent from this list is the life expectancy of lamps, which differs extremely between incandescent lamps (averaging less than a year) and LED lamps (averaging closer to ten years). When considering the purchasing price of a bulb, an informed consumer would consider the purchasing price per functional year and not just the price itself. Agents in our simulation do not have this capability and just look at the price.

The reason that lifetime expectancy has not been included in the lamp satisfaction formula is twofold. Firstly, Kattenwinkel’s reference study has identified it as a lamp attribute which does not significantly affect consumer decisions (Chapter 6.1 of [2]). This led to it not being included in the lamp satisfaction formula. Secondly, the initial idea was to include a satisfaction penalty for when lamps break before their expected point of failure. With this method in place, there was no need to also include life expectancy in the lamp satisfaction formula. However, due to the implementation becoming too
convoluted, this idea was discarded later on, leaving both the expected lifetime and the actual lifetime out of the scope of agent experience.

While the absence of lamp lifetime in the lamp satisfaction determination may prove to be inconsequential because of the non-significance found in Kattenwinkel’s results, to me this is counter-intuitive and something which, given more time, should be improved in the model. The longevity of LED lamps is, together with their efficiency, a mayor selling point and should be a possible consideration for an informed consumer.

The second issue is the method of working with “anti-conformists” in the model. Currently, the distinction between a conformist agent and a anti-conformist agent may be a single percentage point. At every place in the model where a different approach may be chosen by an anti-conformist agent, such as the social satisfaction determination in Chapter 3.6.2 or the social strategies in Chapter 3.7, a cut-off point of social agree-ability $< 50$ determines an agent is anti-conformist. This is for obvious reasons not a realistic assumption. Instead of the binary duality in the current model, a more reasonable approach would assume a broader spectrum of conformism and perhaps have some weighted approach to determining the direction and amplitude of opinion change. To me it seems likely the extremely differing behaviour of the “anti-social” groups in the experiments can at least partly be explained by this artificial duality. The results of the model are not voided by this implementation choice, because we can safely claim anti-conformist consumers do exist and do exhibit behaviour purposefully directed away from the mean. While it may not be realistic to employ a single cut-off point, assuming a threshold does exist in some form is not unreasonable.

The third possible improvement to the model addresses an important outside influence that has not been incorporated in the model: advertising. I think that advertising may explain the gap we have consistently found in the predictions the model makes for LED lamp market penetration and the real-world data suggesting a much higher LED lamp prevalence. As early as 2006, Oxxio, a Dutch energy provider, advertised with discounted LED lamps for their customers\textsuperscript{2}. LED lamps have been brought to the attention of consumers through efforts of the government, producers, purveyors and other interested groups. This form of social interaction is not present in the current model.

I think including targeted and purposeful social methods designed to change consumer opinion into the model is the most important improvement to the current model. It would be very interesting to see a comparison of the results of a model which includes

\textsuperscript{2}Their website at the time is available through the Internet Archive: http://web.archive.org/web/20061116065038/http://www.oxxio.nl/0xxio/Thuis/Producten/Lamp/
advertising to the results of the current model. My prediction is that advertising will largely account for the difference in magnitude that we have observed in the model predictions and the real-world data. This would be consistent with the conclusions of the experiments, which were that “drastic outside involvement” is needed to get people interested in lighting.

Possible implementations of advertising in the model include treating it as a special kind of social encounter and allowing product “specials” to influence the agents during the replacement process. In the first option, an agent encounters advertising and updates opinions towards (or away from) the intended message. This could be very helpful for pushing a lamp that agents are not even aware of exists, when they are engaged in a “repetition” loop. The second possible implementation could include providing temporary price drops, free samples and other substantial benefits which in effect cause agents to abandon their intended behavioural strategy for an other. If an agent does not care much about which lamp it picks, likely little persuasion is needed to change its selection: a 20 percent discount sign might do the trick.

These proposed implementations affect the opinions and product selection of an agent. Possibly, these effects are not far-reaching enough to fully model the influence advertising can have. An opinion adjustment about a product does not increase interest in the product group itself. For example, an agent may have a very high opinion of LED lamps but still not care about lighting in general, because any lighting will be satisfactory. I feel advertising may even raise ambition levels of individuals and secure their interest. Advertisements can make people care about a product. To me, this suggests outside influences such as advertising may need a more fundamental position in the model.

9.2.7 Main question I: implementing a multi-agent system

(I) How can we implement a multi-agent system to aid the analysis of the lighting market based on the Consumat II model?

The wording of the main question as shown above entices to answer it simply with “like so”, meaning it can be done just as shown in this thesis. Instead of this answer, a summary of the answers to the sub-questions will be provided, supplemented with important aspects not yet discussed.

The representation and incorporation of domain-specific knowledge in the model is well-balanced between (a) the ideal theoretic separation of the pure Consumat model on the one hand and the domain-specific application of the model on the other hand and (b) the blending of model and domain to achieve the most efficient computer implementation.
This has resulted in a fast enough computer implementation which can still be adapted to a new application with relative ease. This balance is an important design choice which must be made of every new model or implementation based on the specific project requirements.

Throughout the design and implementation, choices of consumer characteristics and social model have been based partly on data from previous studies and partly on informed conjecture. Every assumption included in the model has been clearly labelled in this document and substantiated when possible. This does not present a weakness in the model, but does show a difficulty for computer modelling in general: data is always sparse. When simulating reality, a modeller prefers to have all data available. This leads to difficult and specific questions such as "how does social interaction affect consumers of the lighting market exactly?". On the other hand, this indicates the power of such models: if we include an assumption about social interaction and the subsequent model shows realistic behaviour, our social interaction idea gains credibility.

One additional merit of the model is its transparency when looking at the model behaviour. The simplicity of the core Consumat model allows an in-depth analysis of why the agents in the model behave as they do. This is an extremely valuable trait, as we have seen in Chapter 6. In this chapter, an error was found in the model which resulted in one particular lamp type being the favourite lamp for every agent in the model, independent of individual agent characteristics. By analysing the model equations, the behaviour of the model was explained and the error could be corrected.

The behaviour of our model conforms to reality when looking at the trends in the lighting market. It likely underestimates the speed of LED lamp adoption, which could be explained by the absence of advertising and other strong outside influence in the model. The results and conclusions drawn from the experiments are in line with the results and conclusions drawn from Kattenwinkel’s market research [2], data of which was used to parametrise and initialise our model.

### 9.3 The domain-specific research questions

To answer the second question of this thesis, *how can we facilitate adoption of energy-efficient technologies in the lighting market?*, again we will first answer the sub-questions II.a and II.b to later return to the main question.
9.3.1 II.a: stable points

(II.a) Where are the stable points (i.e. the possible final states) in the model and which variables affect these in what way?

In the simulations we have run, no situation has been encountered in which a stable situation did not eventually occurred. By “stable” we do not mean that the situation does not change at all, but we mean that the lamp token distribution remains relatively static, resulting in a stable graph. Examples of this can be seen in Figure 7.1, Figure 7.23 or Figure 8.10.

In the homo economicus model we see a stable stable state being reached quickly; every agent deciding which is the best lamp and not deviating from this selection. In the functional model the effects of repetition become immediately clear, the stable situation being for a significant part dependent on the random initialisation. In the full model, this initialisation-and-repetition effect is still apparent, but the social strategies and encounters result in a more dynamic distribution and a longer time until stabilisation.

Initially, the most popular lamp is the same in each model variant and is selected based on its lamp characteristics. Depending on the availability of the “repetition” strategy, changes in the market propagate immediately to the homes of the consumer (as in the homo economicus model) or very slowly to not at all (as in the functional and full model). This means that the availability of strategies and the strategy selection of agents are a large influence on the stability and final state of the model.

The effects of habitual behaviour especially shape the resulting lamp distribution. Agents not engaging in the “repetition” behaviour are exposed to different and possibly new types of lamps through functional or social means, whereas agents with repeating behaviour are content with their current situation and do not wish to invest energy in other behavioural options.

We have seen that anti-conformist agents are the first to change strategies and adopt new lamps. The individual characteristics of agents determine in part their selected strategy and thus the types of agents are also a contributing factor to the final model state.

So in answer to question II.a, we can say that lamp characteristics determine which lamp will be most popular initially, but agent characteristics determining behavioural selection and especially the “repetition” behaviour determine the lamp distribution under changing market circumstances.
9.3.2 II.b: technology diffusion

(II.b) How does the social model affect the diffusion of new technologies?

To answer this question, we will compare the functional model to the full model. The relevant chapters for the functional model are Chapter 7.2 and Chapter 8.3. For the full model, these chapters are Chapter 7.3 and Chapter 8.4.

In the *homo economicus* model and the functional model, each agents act as if it is the only person in existence and is not influenced by others. The social strategies and social interaction allow agents to directly and indirectly influence each other. Among other effects, the social complication results in a much longer stabilisation time because changes in the agent population have a “second order” influence.

The most significant influence of the social strategies can be seen in the anti-conformist group. The difference between the average strategy selection and the anti-conformist strategies is neatly illustrated in Figures 7.24 and 7.25 and Figures 8.11 and 8.12. These show the anti-conformist group does not engage in “repetition” nearly as often as the other groups and relies heavily on the social strategies (as best seen in Figure 8.12).

In the experiments, we see that the social encounters and the social strategies in particular aid the adoption of new technologies. Anti-conformist agents are driven towards new options and can in turn influence other agents to select the same. This is demonstrated in Figures 7.16 and 7.31, showing the stable situations after the reintroduction of a removed lamp for the functional and full model. In the functional case, the previously popular LED lamp does not regain its dominant position due to habitual behaviour. In the full model, this stagnant situation is prevented by the social strategies. However, as mentioned before, the changes due to social behaviour are very slow and take a long time to stabilise.

The slow effects of the social model become especially apparent when comparing the realistic full simulation to the estimated true situation: the diffusion of new technology in our model is behind on developments in the real world. So while the social model aids adoption of new technologies, it does not result in fast enough change. This suggests that either the social effects in the lighting market are much stronger than those included in our model, or that one or more other factors help facilitate LED lamp propagation. As discussed in Chapter 9.2.6, advertising may be one such factor.

So to answer question II.b, we can say the social encounters and especially the social strategies aid the diffusion of new technologies by presenting an alternative to simple repetition. Socially-aware agents and anti-conformist agents in particular are more likely
to notice market changes and act on them. However, based on our experiments we can say that the used social model alone is not enough to explain the magnitude of the observed changes we currently see in the lighting market.

9.3.3 Main question II: adopting energy-efficient technologies

(II) How can we facilitate adoption of energy-efficient technologies in the lighting market?

In the *homo economicus* model, we have seen that the purely economic man is always aware of the market conditions and takes the time to select the very best option from all possible products. If this were the real situation, the only way to get the consumer to purchase energy-efficient products is to make it the most appealing alternative, either through intrinsic qualities or external benefits such as subsidising. Knowing that LED lighting is currently the most economically and environmentally appealing alternative, no other incentive would be needed to convince consumers to switch to LED lighting if all consumers acted as the *homo economicus* model indicates.

Once we introduce the “repetition” behavioural strategy in the functional model, the motivational issue becomes clear. Most agents are quickly satisfied with their lighting arrangement and lack the motivation to invest energy in improving their situation. Consumers stuck in repeating behaviour are hard to reach without social influences. The only way to force a repeating agent to reconsider its strategy is to change its favourite product for the worse. If a product becomes less desirable, for example by raising prices, an agent could become dissatisfied and change its behaviour. If a product becomes unavailable, an agent is forced to change strategies. This is the intended effect of the European Union’s prohibition of certain types of incandescent lighting.

With the introduction of social influences in the full model, we gain a new mains to influence the consumer, not directly relating to changing the market itself. Through the social interaction and social strategies agents become aware of the selection of other agents and their position in the community, which can provide an extra stimulus to invest time and effort into products not functionally interesting to the agent. This effect alone has resulted in a far better adoption of LED lamps in our experiments. Exploiting social influence through purposeful methods such as advertising could result in faster adoption.

In our experiments, adoption of new and energy-efficient lighting does occur, mainly through social influences. However, the diffusion is very gradual because most agents are content with their current lamps and simply keep purchasing the same types. We
have seen that changing the market works only if the old favourites are affected: just making a new alternative appealing does not reach the habitual consumers. Also social influences can motivate a functionally not ambitious consumer. Once a consumer does replace a lamp with a better alternative, this change is likely to be permanent.

Reaching the habitual consumer is key in changing consumer behaviour in the lighting market. Banning their favourite bulb is one effective way of reaching these consumers, but this method is expensive, invasive and difficult to implement. If we do not want to force a change to the most popular product, we can not change the behaviour of repetitive consumers by making the alternative more appealing, because it would still require effort on their part to discover the appeal.

In this thesis, we have investigated the reasons why consumers are not adopting energy-efficient lighting. While the model can be used to investigate possible solutions, unfortunately in this study we do not have the time. We can however give some recommendations based on our findings:

Convincing people to invest in energy-efficient lighting is a problem of getting a satisfied, disinterested and thus lazy consumer to change its behaviour – a difficult group to reach. Any effort to promote energy-efficient lighting should thus be targeted to the lazy and uninterested.

9.4 In conclusion

The most important conclusions of this thesis are:

- Habitual behaviour is the most prominent reason for lack of adoption of energy-efficient technologies in the lighting market.

- Social behaviour helps facilitate diffusion of new technologies in the lighting market.

- The developed model replicates behaviour as observed in the reference study [2] and can confirm its conclusions.

On the internet, a website http://www.lolmythesis.com can be found on which students can summarise their thesis in a single short sentence. Examples of this include:

“Fish are less grumpy after they eat.”
for a biology thesis,

“People on the other side of the world talk differently”

for a linguistics thesis from the University of Leiden and

“Immunosuppressants suppress immune cells”

for a thesis in medicine.

In this spirit, I would like to present the final conclusion of my thesis:

- People are not really interested in lamps.
Bibliography


