Uncontrolled Degassing of Ships

An Agent-Based Approach

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Preface

For me, the final section I will write for this report, for readers, likely the initial section they will encounter. Reflecting on the path that got me here evokes some strong sentiments. I contemplate the growth I have undergone, not only academically but also personally. While the journey was not always smooth, I ultimately emerged victorious, and this thesis stands as a testament to that triumph.

Undoubtedly, the completion of this work would not have been possible without the invaluable support of several people, and I would like to express my gratitude to them. First and foremost, I would like to thank my first supervisor, Haiko, whose patient guidance shaped the course of this research and this thesis. Despite the importance of a thesis, he consistently offered a reassuring perspective, viewing it as just another step in the academic journey. I am also grateful to the IDLab team, particularly Stephanie and Paul, for their unwavering supervision and dedicated hours invested in assisting me with my research. My time at the IDLab was truly fulfilling, transforming me from a novice intern to the temporary ABM expert of the IDLab in a remarkably short period. Also, I must acknowledge my second supervisor, Martijn, whose experience proved invaluable in refining various aspects of the model.

On a more personal level, I would like to thank my parents for their unwavering support, enduring through the extensive period of my studies. Throughout my thesis, I occasionally overlooked the need to take a break. Fortunately, through the years, I met some wonderful friends who were consistently able to divert my attention from my thesis. Lastly, I want to express my deepest appreciation to my girlfriend, Lotte. It would be an understatement to say that I could not have done this without you. As I conclude this thesis, I eagerly anticipate the next chapter in my life.

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Executive Summary

The concept of deterrence, using fear of punishment to encourage compliant behavior, is widely discussed. However, deterrence often places an emphasis on the economic side of compliance while neglecting other possibly crucial factors, as is argued by the literature. Psychological factors, notably the personal norm and the social norm, often appear to play important roles in the decision to comply or not. The personal norm describes an individual's attitude and moral stance toward specific behaviors, such as compliance. On the other hand, the social norm revolves around perceptions of others' behavior and opinions within one's social network. To explore these psychological factors and their impact on deterrence, the research question is framed as follows:

> ***Research Question:*** *What is the effect of deterrence on compliance rates when a population's decision-making can be influenced by social and personal factors?*

The research question will be divided into the following sub-questions: How can decision-making regarding compliance behavior be described, considering personal and social factors? What is the influence of different population compositions, with different fractions of actors following a certain image, on the effect of deterrence? What influence does an environment that enables or impedes compliance have on the effect of deterrence?

Agent-Based Modeling (ABM) is chosen as the method to research these questions. In Chapter 3 Agent-Based Modeling is explained along with its strengths and weaknesses. The strengths of Agent-Based Models (ABMs) lie in dealing with complex, heterogeneous, non-linear systems in a fairly simple manner. However, weaknesses include difficulties in validating a model due to the high demand for data to validate such a system, but also, the computational expense, the lack of generalizability, and the accessibility can limit the use of ABM. Still, Agent-Based Modeling can be useful as by specifying the behavior of a single agent, a whole system can be explored, making it a suitable method to describe a social system. Hence, it is used to provide a platform to combine the Theory of Planned Behavior with the Rational Choice Theory to establish the decision-making behavior, combining social, personal, and economic factors.

Together with the Inspectie Leefomgeving en Transport (ILT), a case study is done to study the complex social phenomena that are expected from studying deterrence in a real-world context. The case concerns the illegal degassing of tanker vessels, as specified in Chapter 4. These ships transport Volatile Organic Compounds (VOCs) that leave some gas after unloading. However, subsequent loads are not always compatible with the remaining gas. Therefore, a ship might need to degas, which it can do legally or illegally. Illegal degassing is significantly more efficient and economically beneficial. Hence, it is an option that is chosen quite often. Right now, only one substance is banned, but a ban on a few more substances is scheduled for 2024, increasing the need for regulation. A few options can be explored to regulate the new ban: enhancing the environment to allow for easier legal degassing or focusing on deterrence. This allows for the case to be very flexible in exploring different strategies and see how they affect the compliance rates of the population. In turn, this case study can give practical insight into the decision-making.

The combined framework, the effect of deterrence, and the case study will be explored with the help of ABM. In Chapter 5, the steps towards conceptualizing the ABM are discussed. The output of interest, the Key Performance Indicator (KPI), will be the non-compliance rate. Hence, the amount of illegal degassing that takes place over the total amount of degassing. The agents that will be represented in the model will be the ships and the inspectors. The ships are the agents that will perform the behavior related to the RCT and TPB framework. In the model, two of the three images of compliance will be characterized: The Amoral Calculator (AC) and the Political Citizen (PC). This is because the Organizationally Incompetent (OI) is often associated with complex organization structures or regulations, which is assumed not to be the case. Also, according to the literature, they are not sensitive

to deterrence and not to social or personal norms. Hence, they would have a small role in exploring the regulation strategies and might only delay the convergence of the model. The inspectors will be there to punish the non-compliant agents and as a proxy for most of the regulation strategies. Also, the degassing stations are modeled as objects together with the harbors. The RCT-TPB framework will consist of two contradictory Multi-Attribute Utility Functions (MAUFs). Each factor, economic, social, personal, and control, will have a weight that depends on the image of the agent. The social norm, as well as the certainty of punishment, will be perceived through the social network of an agent.

In Chapter 6 the formalization of the model is described. This includes a narrative of the model, which is supported by a Business Process Model Notation (BPMN) of the model. Variables are described along with a range of possible values, and a visualization of the model is given. Several steps were taken to verify the model to ensure it works properly and that the results from the model are not caused by errors in the model. Also, the model will be calibrated on the data acquired from different sources (e.g., the ILT), and some of the base parameters are listed. Validation, however, is not performed within the scope of this research. Nevertheless, ways to validate the model are described.

After the model is formalized, experiments are run. As described in Chapter 7, three types of experiments will be performed. First, a Sobol analysis, a global sensitivity analysis, is used to gain insight into the contribution of certain parameters to the output variation. Then, short-term runs are performed to observe the direct influence of deterrence on a population. These experiments will be done under the influence of two different environments, an environment with One Degassing Station (1DS) and with Three Degassing Stations (3DS). Also, six different population compositions will be tested. Finally, the indirect effects of deterrence will be researched through a series of long-term experiments. Again, these experiments will be done for the two aforementioned environments but with only four different population compositions.

The results are then discussed in Chapter 8. From the Sobol analysis, it became clear that the biggest contributors to the output variation were the fine cost, the punishment probability, and the number of degassing stations. For the short-term experiments, a clear difference in sensitivity to deterrence is observed between the two different types of agents. ACs are significantly more sensitive to deterrence than PCs. Also, differences in the effectiveness of deterrence are noticed when the environments are changed. Where the 1DS scenario shows a limited achievable compliance rate for every mean of deterrence after a certain point, the 3DS case does not, allowing for much higher compliance rates. The same limit for the 1DS scenario can be observed for the long-term runs, while the 3DS scenario easily passes that limit. So, a clear positive contribution to the effect of deterrence on the compliance rate is shown for the environment enabling compliance. The measures with the biggest effect were shown to be the certainty of punishment instead of the severity of punishment. Less clear is the indirect effect of deterrence. What was expected is that by deterring individuals sensitive to deterrence, the group less sensitive toward the social norm would follow suit and increase compliance. However, there was little indication (e.g., specific scenarios) that this was actually the case. Hence, no unambiguous conclusion could be drawn from this.

Still, the model delivered some insights that led to implications for the ILT, but also for the framework that was used, as is specified in Chapter 9. From the results, it became clear that the current environment does not provide sufficient opportunities for degassing legally. Lacking these opportunities will limit the levels of compliance that can be reached, no matter what deterrence measures are used. Hence, providing these opportunities is vital when regulating the degassing of ships. Hereafter, a way has to be found to increase the certainty of punishment slightly. Similar to the literature, the model also shows a greater benefit to the certainty of punishment, and without it, the opportunities to degas legally will not be utilized even when provided.

The combined frameworks of the Rational Choice Theory and TPB had an overall positive performance. Key elements from the literature could also be concluded through the model's results, for instance, the ineffectiveness of deterrence on PCs. However, the implementation still showed some limitations. The personal and social norms were argued not to be robust enough, which might explain the inability of the model to provide a more clear observation of the indirect effect of deterrence. Also, inspections only covered the economic side of deterrence, while there is various literature on the psychological effect of punishment, which the model thus lacked. Studying and improving on these limitations are, therefore, given as a recommendation for future research. Also, adding shipping companies is recommended as a research opportunity for the ILT.

Finally, in Chapter 10, conclusions from the research are drawn by answering the research question and sub-questions that were stated. Starting with the different compositions of the population, from the research, it can be concluded that populations with a higher fraction of Amoral Calculators are more sensitive to the effect of deterrence. This is mainly due to the ACs being highly sensitive, not necessarily through the interactions between the different images. Furthermore, from the variations in environment, it could be concluded that an environment with better compliance opportunities will also show a greater effect of deterrence on the non-compliance rate. Then, the RCT-TPB framework showed a promising performance regarding the exploration of deterrence, as some critical conclusions from the literature were also shown through the model results. Improvements can still be made, which indirectly leads to the answer to the main research question. Little evidence was found for effects other than the direct effects of the deterrence policies. However, there were cases in which the indirect influence of deterrence, at least through social factors, seemed to affect the compliance rates. This means that regulations targeting specific types of people could indirectly, through personal and social norms, influence the compliance rates of a whole population

List of Acronyms

1DS One Degassing Station
3DS Three Degassing Stations
ABM Agent-Based Model / Agent-Based Modeling
AC Amoral Calculator
AIS Automatic Identification System
BA Barabási-Albert
BPMN Business Process Model Notation
EMA Exploratory Modeling and Analysis
ER Erdös-Rényi
ILT Inspectie Leefomgeving en Transport (Human Environment and Transport Inspectorate)
IVS Informatie- en Volgsysteem (Information- and Tracking System)
KPI Key Performance Indicator
MAUF Multi-Attribute Utility Function
MF Muelder and Filatova
OI Organizationally Incompetent
PBC Perceived Behavioral Control
PC Political Citizen
RCT Rational Choice Theory
RR Robinson and Rai
SALib Sensitivity Analysis Library
SE Schwarz and Ernst
TPB Theory of Planned Behavior
TRA Theory of Reasoned Action
VOC Volatile Organic Compound
WS Watts-Strogatz

Nomenclature

A	Attitude towards a behavior
b	The strength of an individual's belief
c	Control belief
C_{fine}	Perceived cost of the fine
C_F	Fine cost
C_{time}	Perceived cost of the time lost
e	Subjective evaluation of each belief
f_j	The punishment a person expects
IDC	Illegal degassing count
IDC/TDC	Non-compliance rate
k_n	Nearest neighbors in a network
m	Motivation to comply with the norm
m_n	Edges in a network
n	Normative belief
n_n	Nodes in a network
n_s	Number of scenarios
O_j	The number of offenses a person would commit
p	Power of the control factor
P_{caught}	Perceived probability of being caught
p_j	The probability of conviction a person expects
p_{m_n}	Probability of forming an edge in a network
P_{punish}	Punishment probability
p_s	Number of parameters to be examined each scenario
PBC	Perceived Behavioral Control
S_i	First-order sensitivity index
S_{T_i}	Total sensitivity index
SN	Subjective Norm
$t_{illegal}$	Time spent if degassing illegally
t_{legal}	Time spent if degassing legally
TDC	Total degasssing count
u_{eco}	Economic utility
$U_{illegal}$	Total utility of performing illegal degassing
u_j	An overarching variables representing the influence of all other factors
U_{legal}	Total utility of performing legal degassing
u_{pbc}	Perceived Behavioral Control utility
u_{pn}	Personal norm utility
u_{soc}	Social utility
V	Output Variance
V_{ij}	Contribution of the interaction of parameter i and j to the output variance
V_i	First-order contribution of parameter i to the output variance
w_{eco}	Weight for the Economic utility
w_{pbc}	Weight for the Perceived Behavioral Control utility
w_{pn}	Weight for the Personal norm utility
w_{soc}	Weight for the Social utility

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1
Introduction

Increasing the risk of participating in non-compliant behavior and, thereby, scaring people to prevent them from doing so, in short, deterrence. The idea originated in the 18th century. When dealing with rational individuals, if the possible negative consequences of non-compliant behavior are unattractive enough, one should not want to participate in that behavior (Beccaria, 2006)[1]. So, increasing the certainty and severity of punishment would deter people from committing crimes. This idea of deterrence was revived in the 1960s in the form of the Rational Choice Theory (RCT) (Becker, 1968). However, individuals were not assumed to be perfectly rational in this theory. Decisions would be made on a rational basis within the knowledge of an individual and one's perception of the costs and benefits.

By economically approaching the offending of regulations, the RCT assumed that the number of offenses would be decreased whenever the certainty or severity of punishment was increased. Other factors were acknowledged to have an influence as well but are assumed to be constant (Becker, 1968). These factors include, for instance, willingness to commit an offense and income from legal activities. In the years after, compliance research did find relations between the certainty and severity of punishment and compliance. However, other factors that were first assumed to be constant proved to be influential on the compliance rates. Mostly, the personal norm, consisting of personal morals and willingness to perform specific behavior, proved to be an important indication of compliance (Wenzel, 2004). Also, the social norm an individual perceives, what others do or expect the individual to do, is mentioned as a determinant for compliance. Moreover, it was discovered that individuals valuing these psychological factors over economic factors are less influenced by deterrence (Kagan & Scholz, 1980). These insights often raise the question of whether increasing deterrence is the best way to ensure compliance, especially since there are limits to increasing deterrence. Still, it is an often-used policy.

Hence, the effects of deterrence will be studied during this research. However, not only the economic component but also the psychological components, meaning the personal and social norms, will be considered. The research question to be answered, together with the sub-questions, are discussed in Section 1.1. These questions follow from the literature, which is reviewed in Chapter 2. From the literature, a framework is recognized that is often utilized in social studies. Namely, the Theory of Planned Behavior (TPB), which inherently considers the personal attitude towards specific behavior and the subjective norm as indicators for intention to perform that behavior. The TPB will then be enhanced with the RCT to combine psychological with economic aspects. This method will be described in Chapter 3, together with Agent-Based Modeling (ABM) as a method to explore the framework in an attempt to find answers to the research and sub-questions. Then, these methods are employed in a case study, which is presented in Chapter 4. The case study is done in collaboration with the Inspectie Leefomgeving en Transport (ILT) and is selected due to some essential characteristics. Next, a model is conceptualized and formalized in Chapter 5 and 6, respectively. Subsequently, experiments are described in Chapter 7. The results of these experiments are shown in Chapter 8, after which they are discussed in Chapter 9. Included in the discussion are the implications for ILT, the performance of the framework, and future research opportunities. Finally, a conclusion is drawn, and the research question is answered together with the sub-questions in Chapter 10.

[1]Translation of Beccaria's work from 1764

1.1. Research question

Becker (1968) argued that crime rates can decrease by increasing the probability and severity of conviction if all other variables are kept constant. However, those variables are often not constant as they can differ for each individual and are scenario-dependent. This causes various people to react differently to deterrence, which can also vary for diverse scenarios. Some will be sensitive to deterrence, while others will adhere to their personal norms or perceived social norms and will ignore deterrence. However, that is when considering solely the direct impact of deterrence. Indirectly, deterrence measures might change the perception of social and personal norms. For instance, by affecting a fraction of the population sensitive to deterrence, the perceived social norm of those less concerned with deterrence might be influenced. Thereby possibly indirectly changing their stance on compliance. Hence, the research question is the following:

> ***Research Question:*** *What is the effect of deterrence on compliance rates when a population's decision-making can be influenced by social and personal factors?*

1.1.1. Sub-questions

To answer the research question, it will be broken down into sub-questions. The first, and probably the most important aspect, is to find a way to explore why people make certain decisions, in this case, the decision whether to comply or not. Essential is the ability to consider not only economic factors in the manner of the Rational Choice Theory (RCT) but also the psychological aspects, being the personal and social norms. The decision-making behavior has to take into account all the above-mentioned factors. Additionally, the decision-making behavior should be modular based on differences in values given to the different aspects. Hence, an important question to answer is:

> ***Sub-question 1:*** *How can decision-making regarding compliance behavior be described, considering personal and social factors?*

Secondly, how people react to certain regulations is different and depends on many factors. As Kagan and Scholz (1980) mentioned, some are more driven by economics, and others are naturally more prone to comply. Deterrence focuses its direct effect on the fraction of the population that is sensitive to deterrence. Theorized is that indirectly, it might shift the social norm in favor of compliance, which in turn can affect actors that value the social norm highly. Therefore, the images of Kagan and Scholz (1980) will be assumed. However, that may depend on the size of the group that is actually sensitive to deterrence. If a small portion of the population is actually affected by the deterrence measures, it is unlikely that it will reflect through the population. Hence, to explore the influence of the composition of the population on the indirect effects of deterrence, the following question has to be answered:

> ***Sub-question 2:*** *Assuming the images of Kagan and Scholz (1980), what is the influence of different population compositions, with different fractions of actors following a certain image, on the effect of deterrence?*

Finally, actors make decisions based on their perception, which can, for instance, be their perceived probability of being caught or the perceived social norm, but also the perceived ability to comply. This relates to the reasonableness of regulations. It is not unlikely that people will be less willing to comply if there are unreasonable circumstances for compliance. This might show some relevant insights, especially during this case study. So, the thought is that a situation where it is easier to comply will enhance the impact deterrence has. In the case study, the environment may affect the perceived ability to comply, so the question is whether an environment that enables compliance will also positively influence the impact of deterrence and overall compliance. Hence, this results in the third sub-question:

> ***Sub-question 3:*** *What influence does an environment that enables or impedes compliance have on the effect of deterrence?*

1.2. Relevance for Management of Technology

The Management of Technology program places an emphasis on navigating technological innovations within social and corporate environments. The program essentially teaches the skills to address complex systems and the associated challenges. During this research, such a complex system, namely a population of different actors with different ideas and values, will be discussed. This study holds significance in the context of Management of Technology due to its exploration of complex systems and decision-making processes. These aspects are significant in the management of businesses and the implementation of innovation, where diverse individuals with varying ideas and values are involved. The research specifically considers decision-making regarding compliance, which is, of course, a necessary element as companies navigate internal compliance with organizational regulations and external compliance with industry standards. However, perhaps of greater significance is the exploration of the different aspects of decision-making in an attempt to gain a more comprehensive understanding of the motivation behind decisions, which can be beneficial in the technology management context. For instance, when examining the factors influencing the willingness or reluctance to support specific innovations and changes. Therefore, exploring different components regarding decision-making within a complex system, whether related to compliance or other management aspects, holds significant value for the Management of Technology program.

2
Literature Review

As already mentioned in the introduction, deterrence, although widely used, is not just a simple solution to enforce compliance. There is a lot more to it, especially when taking into account social and psychological aspects. However, first, an understanding of the principle of deterrence is necessary, together with the thought process that led to this concept. Therefore, the early stages of deterrence theory will be reviewed in Section 2.1 until Rational Choice Theory (RCT) in Section 2.2. Next, different images of individuals are discussed in the context of compliance, with their respective reactions to an approach like the RCT in Section 2.3. This is used to connect theories in deterrence with the influence of psychological factors, like social and personal norms, and perception, which are discussed in Section 2.4 and Section 2.5. Then, the negatives of deterrence are mentioned in Section 2.6. Finally, in Section 2.7, the Theory of Planned Behavior (TPB) is explained and argued to be a valuable addition to the RCT when considering psychological factors together with deterrence.

2.1. Rationality of Deterrence

The idea of deterrence is rooted in the utilitarian philosophy, where individuals are considered to be rational, avoiding pain while seeking pleasure. Therefore, it is assumed that the fear of punishment is enough to keep people abiding by the law. This implies that the cost of non-compliance, comprised of the certainty and severity of punishment, should outweigh the benefits of non-compliance as that would deter a potential offender. These ideas stem from the 18th century when Beccaria (2006) [1] questioned the cruel punishments of that time and the irregular procedures that harness inequality.

In his work, Beccaria (2006) addresses a few things involving crime and punishment. In particular, he argues that punishing someone involves criminal behavior, as you would be taking away something from someone without their consent. Hence, the authority to punish should not be taken lightly and should be with someone representing all of society. Furthermore, it is why punishment should be proportional to the offense; everything that exceeds that limit is considered tyrannical. Proportionality is achieved two-fold; first, it has to scale with the damage done to the public good, and secondly, it has to be proportionate to the advantages a crime can bring someone. If both hold, it should contribute to deterring people from committing crimes. This is often mentioned as the severity of punishment. However, even more important to deterrence than the severity is the certainty of punishment. If punishment is inevitable, even when mild, it will have a greater impression than a far more cruel punishment that seems avoidable since hope could make people blind to the consequences of their actions (Beccaria, 2006). A third factor, although more relevant for deterring people from committing the same offense repeatedly, is the promptness of punishment. This indicates that the time between the offense and punishment should be as little as possible. First, it would be fairer towards the convict since the uncertainty and the loss of freedom would be minimized, which Beccaria (2006) already considers as a punishment. Secondly, the punishment has to be associated with the crime so that the link will deter the culprit from committing that crime again. The shorter the period between crime and punishment, the stronger the association and the more effective the deterrent effect.

2.2. The Economic Approach

Beccaria's views were the first steps towards modern criminal law. Still, in the decades after, its influence declined until Becker (1968) decided to try to resurrect and improve this perspective. Becker

[1] Translation of Beccaria's work from 1764

(1968) described criminal behavior with an economic approach, where culprits tried to follow their preferred path, considering the costs and benefits related to that path. This is often referred to as the Rational Choice Theory (RCT) of crime. However, he did not assume people to be perfectly rational. Irrational decisions can be made as people can be led by emotions or are making decisions based on incomplete information regarding the costs and benefits of their actions. This is in accordance with the bounded rationality principle, often used when approaching economics with a behavioral view. However, not being perfectly rational would not withhold a person from making decisions based on an economically rational approach.

He also acknowledges that other non-economic factors influence the number of offenses, for example, genetics and upbringing (Becker, 1968, p. 176). However, he argues that if these factors are kept constant, increasing the probability and severity of punishment will decrease the number of crimes. Similar to Beccaria (2006), Becker also recognizes the certainty of conviction has a bigger influence on the number of offenses than the severity of punishment. Following his approach, the number of offenses by any person can be written as a market function related to the certainty and severity of punishment and the other factors mentioned. This function can be seen in Equation 2.1

$$O_j = O_j(p_j, f_j, u_j) \tag{2.1}$$

O_j is the number of offenses that a person would commit in a certain time, p_j the probability of conviction, f_j the punishment, and u_j is an overarching variable representing the influence of all other factors, including, for example, the attitude towards illegal activities (Becker, 1968, p. 177).

2.3. Images in Compliance Behavior

A similar conclusion was found by Kagan and Scholz (1980), who did a study in which they interviewed regulatory agencies and businesses. They found that there are indeed people who behave and think economically driven. However, based on these interviews, they identified two other implicit theories, so-called images, that explain why businesses violate the law. The emphasis on enforcement differs based on the different theories, and Kagan and Scholz (1980) argue that enforcement based on a single theory is counter-productive in regulating the other images.

The image aligning with the economic approach of Becker (1968) is called the Amoral Calculator (AC) (Kagan & Scholz, 1980). Amoral refers to neutral, not immoral, meaning there is a lack of a moral component in the decision-making, not that this image consciously makes immoral decisions. Following the Rational Choice Theory (RCT), this type is solely driven by profit-seeking. The AC will violate the law if the profits gained by doing so outweigh the fine or the probability of being caught. The key to regulating this type of offender can also be analyzed economically. Severe penalties and a high probability of getting caught by inspecting aggressively are used to deter potential offenders (Becker, 1968; Kagan & Scholz, 1980). In this theory, the role of the regulator is similar to a ”policeman” enforcing regulations without independently judging how bad a violation is (Kagan & Scholz, 1980).

Secondly, there is the image of the Political Citizen (PC). This type is driven by personal beliefs and generally complies with the law. Wenzel (2004) suggests that both personal and social norms play a role when deciding to violate regulations. Personalized norms are described as internalized morals guiding one’s behavior, while on the other hand, social norms are external morals attributed to a social group. Individuals with strong personal norms or close relationships with others, such as family or peers, who oppose criminal behavior are less likely to violate the law (Grasmick & Bursik, 1990; Wenzel, 2004). However, when the political citizen strongly disagrees with regulations or finds them unreasonable, the law can still be broken by this image (Kagan & Scholz, 1980; Bardach & Kagan, 1982). Where deterrence measures, like severe fines, influence the Amoral Calculator, the same measures could have a negligible effect or even the opposite effect on the Political Citizen, as some measures might be perceived as unreasonable to the PC. Instead of a ”policeman” as a regulator, the regulator as a ”politician” is argued to be more effective, to get the Political Citizen and the regulator on the same page (Kagan & Scholz, 1980).

The third image according to Kagan and Scholz (1980) is the Organizationally Incompetent (OI) entity. As the name suggests, this image indicates the inability or incompetence of an organization or individual to comply with the regulations. Deterrence sanctions will not have the desired effect as the incompetent entity is unaware of the mistake. For deterrence to have an effect, one should be aware of the consequences of certain actions, something different literature does agree on (Beccaria, 2006; Becker, 1968). Education is mentioned as the best method to ensure future compliance (Kagan & Scholz, 1980).

2.4. Social and Personal Norms and Deterrence

As acknowledged by Kagan and Scholz (1980), the certainty and severity of punishment are not the only factors found to be deciding one's choice to participate in non-compliant behavior. Other factors like personal and social norms also influence compliance behavior, even more than the economic benefits for certain images. Williams and Hawkins (1986) mentioned that the effect of formal sanctions came largely from them triggering informal sanctions like personal and social beliefs. For instance, Wenzel (2004) found that the only significant relation in the study between severity of punishment and tax evasion was when the social norm strongly condemned that behavior. The importance of a social norm was already mentioned in earlier literature. In a study by Tittle (1977), the fear of losing the respect of people closely connected to the potential offender came up as the second most important variable when predicting future deviance, with only the utility of illegal behavior performing better.

The influence of personal norms is found to be of even greater importance to compliance and the effect of deterrence than legal sanctions or social norms (Grasmick & Bursik, 1990; Bachman et al., 1992; Wenzel, 2004). Grasmick and Bursik (1990) discovered that shame, described as the influence of one's own guilt on one's life, was the factor with the greatest effect when considering non-compliant behavior. The impact of shame was found to be greater than the impact of embarrassment, one's guilt towards others. Wenzel (2004) found that a strong personal view can reduce the impact of deterrence measures, meaning that when someone already condemns a particular behavior, deterrence will have little effect on the decision to participate in that behavior. An earlier study by Bachman et al. (1992) came to a similar conclusion when researching deterrence regarding sexual offenses with a group of male college students. Sanctions were shown to be less effective the higher the moral standard of the students.

2.5. The Role of Perception in Deterrence

As was already mentioned by Becker (1968), the costs and benefits are perceived on a personal basis, as well as the personal and social norms. Everyone has different views, which are bounded by, among others, an individual's knowledge limits. The effect of deterrence differs with different perceptions of probability and severity of punishment (Nagin, 1998). Hence, the perceptive studies (e.g. Kagan & Scholz, 1980; Grasmick & Bursik, 1990; Wenzel, 2004). To study the perceptual side of deterrence, a lot of scenario-based research was done, where people were given certain scenarios with details that could influence the perception of punishment risks, and they had to decide whether to comply or not. On average, the certainty of sanctions would discourage non-compliance, and this was shown for different illegal activities (Nagin, 1998). Also, inexperienced offenders were found to overestimate the effectiveness of enforcement and would, therefore, perceive a higher certainty of punishment, making them less willing to engage in illegal activities. The perception can be updated over time. For instance, when engagement in illegal activities is not punished, the estimation of the probability of getting caught might decline (Lochner, 2007).

Not only does an individual's own experience contribute to the perception of the certainty of punishment, but perceived risks can be influenced by the experience of others close to that individual, like family or friends (Lochner, 2007; Rincke & Traxler, 2011). Rincke and Traxler (2011) researched enforcement spillovers by studying the compliance rates with TV license fees. They found that when a household identified as non-compliant is inspected, its compliance will increase, and its neighbors will also get more compliant. So, an individual's social network influences the perception of the probability of punishment and can change the perception of the costs of illegal behavior.

While for the certainty of punishment, some clear deterrent effects are observed through the perceptive studies, for the severity of punishment, this is not the case (Nagin, 1998; Doob & Webster, 2003). When looking solely at the severity of punishment, there is no deterrent effect coming from severity to be found for most crimes, except for murder (Grasmick & Bryjak, 1980). However, this is also argued to be the cause of the high certainty of conviction for murder. Hence, when the perception of the certainty of punishment is high, there can be a significant effect from the severity of punishment on deterrence (Grasmick & Bryjak, 1980). Still, no consistent direct effects of perceived severity of punishment on deterrence are shown throughout the literature (Doob & Webster, 2003).

2.6. The Negative Effects of Deterrence

As perception, social, and personal norms play a big role in deterrence, a price cannot be put on every unwanted or illegal behavior. It can also have an adverse effect. It might remove certain moral objections towards particular behaviors, inciting people to have a more economical perception. Gneezy and Rustichini (2000) studied this phenomenon by performing an experiment with parents who picked up their children too late from the daycare. The daycare put a fine on the unwanted behavior of being late to pick up the children. However, instead of the expected decrease in observing that behavior, it happened more often. Being late first meant making the teacher stay after class longer, burdening that teacher. Something that was morally condemned. After the decision to fine the parents who were late, it became more of an economic transaction, and the overtime of the teacher became a service. You could pick up your child late if you paid the fine (Gneezy & Rustichini, 2000).

Also, at some point, sanctions might feel unfair. For example, when someone has to spend ten years in prison for jaywalking, that might not feel fair to that person. When sanctions or regulations are experienced as unfair, the support for these sanctions and regulations declines. The risk associated with it is that the willingness of people to comply voluntarily is taken away, and it would lead to resistance (Bardach & Kagan, 1982).

2.7. Theory of Planned Behavior

So, deterrence goes beyond simply increasing the severity and certainty of punishment. As non-compliant behavior is performed by humans, there are specific human traits that influence the effect of deterrence. Individuals' perceptions vary, resulting in different perceptions of costs and benefits and, therefore, differences in decision-making. Factors that influence the perception of an individual can be their own personal norm, so their respective attitude towards the non-compliant behavior, but also the social norm, how others' attitude towards that behavior is experienced. Literature shows positive effects in explaining non-compliance by combining psychological factors and the Rational Choice Theory (Stekelenburg et al., 2023). To explain the psychological factors, the Theory of Planned Behavior (TPB) is chosen as a framework (Ajzen, 1991).

The Theory of Planned Behavior is and extension of the Theory of Reasoned Action (TRA). Ajzen and Fishbein (1980) proposed the TRA as a framework to explain behavior. According to this theory, the key determinant of behavior is the intent to behave in a certain way. This intent is composed of, on the one hand, the attitude towards a behavior and, on the other hand, the subjective norms. Attitude can be described as an individual's positive or negative evaluation of behavior. In contrast, subjective norms refer to the individual's perception of what others think of certain behavior and if that individual feels pressured to comply with the norm. The stronger the attitude towards behavior and the greater the perception that (important) others approve of that behavior, the stronger the behavioral intentions of an individual, and the more likely it is to engage in that behavior. However, one of the critiques of the TRA is that not all factors influencing behavior are considered. External factors can still limit the ability to act on behavioral intentions regardless of their strength, denying individuals complete control over their behavior. Additionally, besides the actual behavioral control, there is the Perceived Behavioral Control (PBC), which is of greater psychological interest, as it refers to one's belief about one's ability to perform a behavior. Therefore, Ajzen (1991) proposed the Theory of Planned Behavior as an extension to the TRA, in which perceived behavioral control was added as a key determinant of behavior. A visual representation of the TPB can be seen in Figure 2.1.

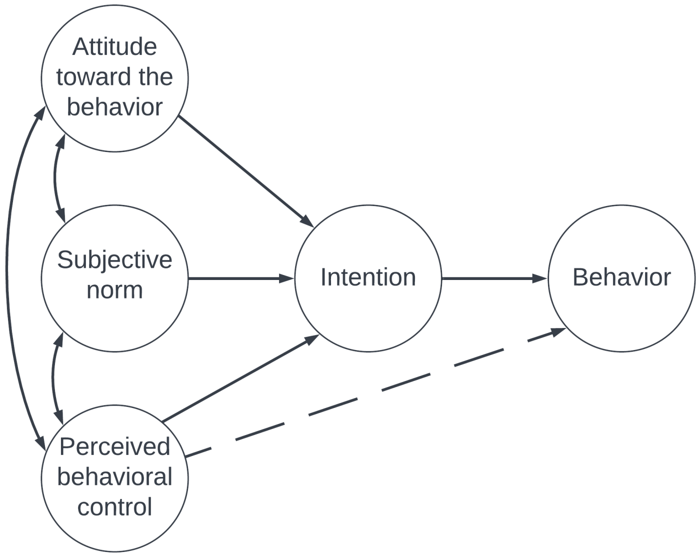


Figure 2.1: Theory of Planned Behavior (Ajzen, 1991, p. 182)

Noteworthy is the direct link between perceived behavioral control and the actual behavior, where prior only the intention had a direct influence on behavior. Ajzen (1991) gives two arguments for that hypothesis. First, considering constant intention, the effort expended to obtain a particular behavior will likely increase with perceived behavioral control. Secondly, PBC can often act as a substitute for the measure of actual behavioral control. However, it depends on the perception's accuracy as a substitute for actual control. Hence, there are conditions where the measure of perceived behavioral control does not influence the accuracy of the predicted behavior, like the lack of information, change in requirements or resources, and new, unknown elements entering the situation.

Ajzen (1991) depicts the TPB with the help of an expectancy-value model, according to which attitude progresses from the beliefs someone holds about the object of the attitude. This is shown in Equation 2.2, where an individual's attitude (A) is directly proportional to the sum of the strength of each belief (b) multiplied by the subjective evaluation (e).

$$A \propto \sum_{i=1}^{n} b_i e_i \tag{2.2}$$

The same is done for the subjective norm, which can be seen in Equation 2.3. The subjective norm (SN) is directly proportional to the sum of the multiplication of each normative belief (n) and an individual's motivation to comply with the norm (m) (Ajzen, 1991). Different aspects of the subjective norm can be considered, for instance, normative (what others want an individual to do, e.g., others expect me to comply) and descriptive (what an individual perceives others to do, e.g., I see that others are complying) (Record, 2017).

$$SN \propto \sum_{i=1}^{n} n_i m_i \tag{2.3}$$

Finally, the Perceived Behavioral Control (PBC) is exemplified in the same manner, following Equation 2.4. The PBC is directly proportional to the summation of each control belief (c) times the perceived power (p) of that control factor, hence the impact a control factor has in performing the behavior. The control belief can cover different aspects influencing the PBC, for example, the capacity to perform a certain behavior (e.g., I am able to comply) and the autonomy (e.g., I am in control to decide to comply) (Sommestad et al., 2015).

$$PBC \propto \sum_{i=1}^{n} c_i p_i \tag{2.4}$$

2.7.1. Compliance and the Theory of Planned Behavior

Combining the attitude, subjective norm, and PBC will give an indication of the intention to perform a certain behavior, which in turn can help to predict the actual performance of that behavior. These factors can be easily manipulated to fit the situation at hand by adding or varying beliefs or the power a belief carries, making it a suitable framework to combine with the RCT.

The flexibility of the framework is, therefore, a reason why it is used more often in compliance literature. For instance, it has been studied regarding traffic regulation compliance (i.e. Parker et al., 1992; Wallén Warner & Åberg, 2008; Moan & Rise, 2011), information security policy compliance (Sommestad & Hallberg, 2013; Sommestad et al., 2015) and tobacco-free policy compliance (Record, 2017). Some studies find strong results in predicting the intentions not to comply using the TPB, whereas others find little evidence. Parker et al. (1992) found a variance in the intention of 42.3% that could be explained by the belief components in the TPB for drinking and driving offenses. Another research, also studying drinking and driving, came to a variance to the intention explained by the TPB between $5\% - 26\%$, depending on the age and sex of the driver, which is significantly lower (Moan & Rise, 2011). Also, the most prominent factors differ per research. For example, when considering two different studies on speeding, one finds the PBC and subjective norm to be most influential (Parker et al., 1992), while another argues the personal beliefs to have more impact (Wallén Warner & Åberg, 2008).

Still, numerous studies indicate a positive performance of the TPB on the prediction of intentions, even more so when extending the TPB with additional components. Sommestad and Hallberg (2013) did a review of papers studying the TPB in the context of information security policy compliance and found an average variance in the intention of around 40% that could be explained by the TPB. Then, Sommestad et al. (2015) found that additional factors, like the ”anticipated regret” and ”threat appraisal”, enhanced the performance by $4\% - 8\%$. So, enhancing the TPB can result in a better-performing framework.

3 Method

Suitable methods have to be chosen to find answers to the research questions. Two frameworks have already been discussed in Chapter 2, which could be used as a method to describe compliance behavior. To discuss deterrence, the RCT is an influential framework. However, to gain a better understanding of the psychological side of deterrence and compliance, the TPB could be a useful framework as well. Hence, an attempt was made to enhance the TPB with the RCT, which will be discussed in Section 3.1. To explore the framework and test it to answer the research and sub-questions, Agent-Based Modeling (ABM) will be used as a method, and its use will be explained in Section 3.2.

3.1. Combining the Theory of Planned Behavior and Rational Choice Theory

From the literature, it became clear that the Rational Choice Theory (RCT) is already widely used in compliance research as an implementation of deterrence. It has proven to be effective in some aspects of compliance. However, it also often fails to explain the influence of social and personal factors, like the behavior of others or an individual's personal morals. On the other hand, the Theory of Planned Behavior (TPB) is a social framework that explicitly mentions the influence of one's attitude, which is connected to one's personal beliefs, and the subjective norm, which is under the influence of the thoughts and behavior of others. Hence, a combination of the two frameworks could enhance the prediction of compliance behavior and could, therefore, be used to describe such behavior.

Interestingly, Wu et al. (2021) integrated the RCT and the TPB in a study considering compliance with medical treatment recommendations. To accomplish this, they omitted the personal norm component and replaced it with a cost-benefit assessment according to the RCT framework. With the integrated frameworks, Wu et al. (2021) accomplished an explained variance for the actual compliance behavior of over 67%. They found strong support for the RCT implementation but not as strong support for the TPB components. However, the compliance that was studied was recommendation compliance instead of regulation compliance, which is the scope of this study. As is shown in the literature, the personal norm is one of the most influential factors in regulation compliance (Grasmick & Bursik, 1990; Wenzel, 2004). So, omitting such a factor from the framework is not expected to be beneficial in predicting compliance regarding regulation.

Hence, instead of replacing the personal norm with a cost-benefit assessment, the cost-benefit assessment is added to the TPB framework, and both of them will represent the attitude component. A representation of the combined TPB-RCT framework is shown in Figure 3.1. The subjective norm will be dependent on the social network, as well as the perceived certainty of punishment. Personal experience will define the personal norm and the perceived certainty and severity of punishment.

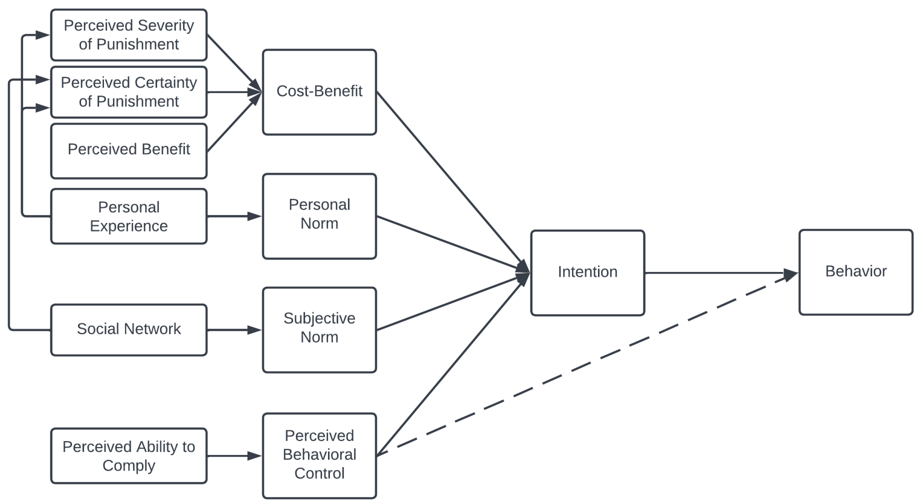


Figure 3.1: Representation of the combination of the TPB framework with RCT

3.2. Agent-Based Modeling

For the exploration of the TPB-Rational Choice Theory (RCT) framework and to find answers to the other sub-questions and the research question, Agent-Based Modeling (ABM) is chosen as the method to do so. The goal of ABM is to gain insights into complex systems by analyzing simulations of that system. A social system like a population under the influence of regulation is considered to be such a complex system. Hence, it was chosen as a method for this research.

Axelrod (1997) compares ABM to the standard methods of doing science, namely induction and deduction. The principle of induction is to identify certain patterns in real-world data, and deduction is based on proving the consequences of an assumed theory. Agent-Based Models (ABMs) are, like deduction, built based on explicit assumptions; however, it does not prove the consequences of these axioms. Alternatively, the data generated by the ABM can be analyzed inductively, giving insight into the workings of the complex system. Agent-Based Modeling can, therefore, be seen as a way to do thought experiments and challenge intuition, as the assumptions might be quite simple. Still, the consequences are not necessarily obvious (Axelrod, 1997).

In an Agent-Based Model, an agent is given a state and a set of rules representing behavior based on assumptions. An agent can, based on the rules it is given, interact with other agents or the environment, which in turn can change the state and the behavior of the agent. Through these interactions and changes, patterns may emerge that were not programmed explicitly (Epstein & Axtell, 1996; Macal & North, 2010). Therefore, Agent-Based Modeling is viewed as a bottom-up approach to modeling complex systems, as emerging patterns are “grown” from interactions following simple rules (Epstein & Axtell, 1996).

An ABM typically consists of three elements (Bonabeau, 2002; Macal & North, 2010). First, a set of agents, including attributes and rules representing their behavior. Secondly, there are ways for agents to interact, hence a set of relationships. Finally, an environment for agents to interact with, additionally to agent-agent interaction.

Macal and North (2010) also mention essential characteristics to be considered when modeling agents. An agent is self-contained; it has boundaries so it is clear whether something is or is not part of the agent or even a shared attribute. Being a uniquely identifiable individual with attributes to be distinguishable and recognizable from and by other agents is also essential for agents. An agent is autonomous and can function and interact independently. Through interaction, an agent can obtain information, and with the behavior, it can relate that information to the actions and decisions of itself, making it autonomous. Agents have a state that can change over time, representing the variables corresponding with the current situation. The state of an agent is represented by a set or subset of attributes, and the behavior an agent has is influenced by its state. Through interactions with other agents, that behavior can also change, as well as through interactions with the environment. Therefore, agents will be able to observe and identify certain characteristics of other agents. Besides these key factors, an agent may also be able to learn and adapt based on a form of memory. An agent may have goals, like maximizing profit, for example. Lastly, agents may be heterogeneous. They can vary in state, behavior, and characteristics over time due to interacting with other agents or the environment (Epstein & Axtell, 1996; Macal & North, 2010).

3.2.1. Strengths and Weaknesses of Agent-Based Modeling

From the literature, several strengths and weaknesses of Agent-Based Modeling are recognized, which are essential to consider when building an ABM. One of the biggest strengths of ABM is the ability to capture heterogeneity, non-linearity, and complexity of systems. Each agent in the model can have different attributes and decision-making rules, which can change as a simulation progresses. For instance, this allows for a more realistic image of human behavior in complex systems (Macal & North, 2010; Axelrod, 1997; Bonabeau, 2002). Besides, it can generate insights and test hypotheses that are otherwise difficult to obtain or test through traditional analytical methods, for example, if traditional methods would be unethical or take a lot of time (Macal & North, 2010; Axelrod, 1997; Epstein & Axtell, 1996). Another advantage of ABM is the flexibility to be used in a wide range of domains like economics, politics, ecology, biology, etc. (Axelrod, 1997; Epstein & Axtell, 1996; Bonabeau, 2002)

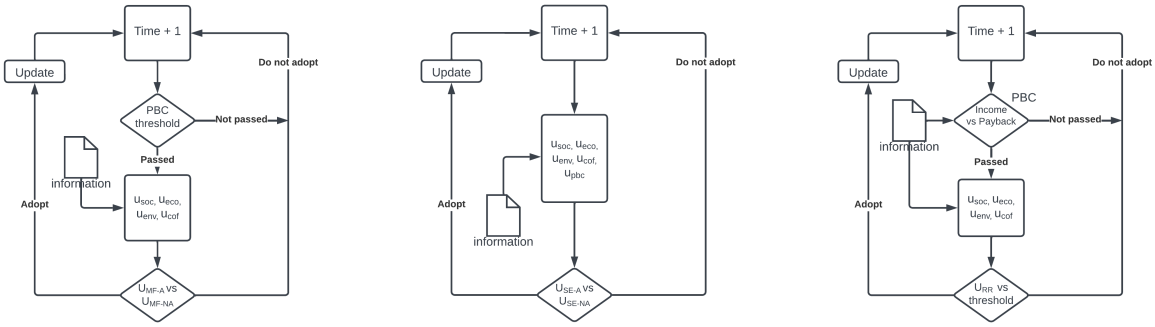
However, there are also weaknesses involved with the use of Agent-Based Models. One of the biggest challenges of an ABM is when modeling a complex system, a lot of assumptions are made for the decision-making rules and the parameters, which makes it easy to introduce uncertainties in the model outputs (Axelrod, 1997; Epstein & Axtell, 1996; Bonabeau, 2002). To make a more robust model, it has to be validated. However, as often stochastic and dynamic processes are involved, it is quite difficult to validate an ABM, and a considerable amount of data would be needed to do so, adding to the difficulty of validation as there is not always sufficient data present (Bonabeau, 2002; Epstein & Axtell, 1996; Axelrod, 1997). Besides, ABMs can be computationally expensive, as every agent could perform several actions every tick, and when models get bigger, the computational requirements can get exponentially higher (Axelrod, 1997; Epstein & Axtell, 1996; Bonabeau, 2002; Macal & North, 2010). To reduce this computational strain, simplifications are often made. However, by doing so, there is a risk of oversimplifying and thereby ignoring valuable aspects important to the system (Axelrod, 1997; Epstein & Axtell, 1996). Another result of oversimplification is that it usually leads to a case-specific model of a particular system, decreasing its generalizability to other contexts (Macal & North, 2010). Finally, it can be very complex to build an ABM as a modeler would have to find a balance between a simple model to reduce computational requirements and a complete model so as not to miss any important aspects and also keep in mind the robustness of the model. Therefore, the accessibility of agent-based modeling is limited and difficult for non-experts (Bonabeau, 2002).

3.2.2. Theory of Planned Behavior in Agent-Based Models

The TPB-RCT framework is mainly a representation of the TPB with an enhancement from the RCT. Hence, the methodological challenge does not necessarily lie in the RCT aspects but in implementing a framework like the TPB in an ABM. Many theories in social sciences are subjective, as is the case with TPB. It consists of attitude, subjective norms, and intentions, which are abstract constructs that can be interpreted in many ways when operationalizing the theory in a model. Hence, Muelder and Filatova (2018) studied the quantitative and qualitative differences between three different implementations of the TPB in an ABM.

They studied household behavior when considering investing in solar panels under the influence of different implementations of the TPB in ABM. As a basis Muelder and Filatova (2018) took an ABM that was used earlier to study the diffusion of renewable energy among households (Tariku, 2014; Muelder, 2016), which they refer to as the *MF ABM*. The base ABM is then compared to two different ABMs, which are also inspired by the TPB, namely Schwarz and Ernst (2009) and Robinson and Rai (2015), referred to as *SE* and *RR* respectively. These three studies were then compared on four dimensions:

Different architecture, different factors, different representations, and different data. All three studies combine the Theory of Planned Behavior with a Multi-Attribute Utility Function (MAUF) to assess the potential utility of investing in solar panels. However, based on architectural differences, the utility function looks different. An overview of the different architectures can be seen in Figure 3.2.



(a) MF ABM (b) SE ABM (c) RR ABM

Figure 3.2: Representation of the TPB architecture in the respective studies (Muelder & Filatova, 2018)

The main difference can be found in the use of the Perceived Behavioral Control (PBC). Both the *MF* and the *RR* studies use the PBC as a barrier, which, if not passed, immediately rejects the adoption of the decision. The only difference is that the *RR ABM* compares the PBC to the expected payback, whereas the *MF ABM* compares it to a random value. The *SE* study combines the PBC with the utility function. The models were run over the course of 30 steps, and in the end, the effect of the architecture did result in differences in the outcome. The diffusion rate observed with the *MF ABM* was 18% and 37% higher than the diffusion rates of the *SE* and the *RR ABMs*, respectively (Muelder & Filatova, 2018). This is partly due to the saturation points, which are for the *SE* and *RR ABMs* relatively early (i.e., steps 5 and 7, respectively), while the *MF ABM* overshoots with a saturation point at step 28.

Besides the architecture, the models were also tested for different factors (availability of information), different representations (type of information, uncertain information, cost information, or no information), and different data (uniform, empirical, normal, and Poisson). The most notable conclusion from these experiments is that the *RR ABM* is significantly more sensitive throughout all these experiments (Muelder & Filatova, 2018).

In the end, a decision has to be made on how to represent the implementation of the Theory of Planned Behavior in an Agent-Based Model. Still, the study of Muelder and Filatova (2018) is not there to convince the reader of the best implementation. Instead, it notifies the reader of the effects of different implementations. Muelder and Filatova (2018) argue that the TPB is a broad and ambiguous concept, and a modeler should be aware of the consequences of their implementation decisions at least until a better understanding of this concept is acquired through dialogue between behavioral sciences and modelers.

4 Case Study

To answer the research question and sub-questions, a case study will be done to gain insight into the theoretical effectiveness of deterrence measures. The case study will be done in collaboration with the Inspectie Leefomgeving en Transport (ILT) and will be about the so-called degassing while sailing case, which will be explained in more detail in Section 4.1. One of the advantages of doing a case study is the flexibility to adapt a case study to a research question, which is demonstrated by the current case. The offense of illegal degassing is, namely, not as condemned morally as, for example, robbery. Therefore, it is a suitable type of offense to study deterrence, as there is potentially better responsiveness to fluctuations in certainty and severity of punishments. Also, this case is ideal for testing for different environments that enable or impede compliance, as the current situation makes it quite difficult to follow regulations, which will be explained in Section 4.2. An often-mentioned disadvantage of performing a case study is the generalizability of the results (Yin, 2018). What can be evident from this research might not translate to every other field. So, this has to be considered when discussing the results later. Furthermore, in this chapter, an actor analysis will be presented in Section 4.3. Information on the data is explained in Section 4.4.

4.1. Case description

When inland tanker vessels transporting a volatile hydrocarbon product (i.e., petrol) unload their cargo, small amounts of product will remain inside the tank in liquid or vapor form. If these hydrocarbons have a vapor pressure bigger than 10 Pa at 20 °C, they are referred to as Volatile Organic Compounds (VOCs) (De Buck et al., 2013). Some VOCs are carcinogenic, harmful to the environment, and even explosive. For subsequent cargo to not get contaminated, ships must be degassed before they can be loaded again. However, degassing is unnecessary when the subsequent cargo is the same or compatible with the previous load. Otherwise, the ship has two options to be degassed: a special installation that removes the residual gas safely ('controlled degassing') or simply ventilating the ship's tanks, which can even be done while sailing ('uncontrolled degassing').

The problem with uncontrolled degassing is that harmful VOCs are released into the atmosphere with all its consequences. Therefore, there is already an EU-wide ban on mobile degassing of petrol (indicated by UN-number UN1203) and degassing VOCs around densely populated areas, bridges, and locks. On a more local level, it is also prohibited, for example, in the province "Zuid-Holland" to release the following VOCs into the atmosphere (Provinciale staten van Zuid-Holland, 2019):

- Benzene (UN1114)
- Petroleum crude oil, with more than 10 percent benzene (UN1267)
- Petroleum distillates, with more than 10 percent benzene (UN1268)
- Aviation fuel, with more than 10 percent benzene (UN1863)
- Flammable liquid, with more than 10 percent benzene (UN1993)
- Hydrocarbons, in liquid form, with more than 10 percent benzene (UN3295)

In Figure 4.1 a map is shown indicating where degassing is prohibited and where it is prohibited unless the ship follows all the ADN (ADN is a European treaty for international transportation of dangerous cargo over inland waters) conditions and local regulations.

Figure 4.1: An overview of waterways in the Netherlands where degassing is regulated.

4.2. Problem for regulation

Although the ban on degassing in densely populated areas decreases the health risks for a large group of people, there are still people living in less populated areas. Besides, the harmful effect on the environment is still an issue. Therefore, there have been plans to put an EU-wide total ban on degassing while sailing. The Dutch government is also planning on banning more substances from uncontrolled degassing. The plan is to start July 2024 with phases one and two, from when the ban will include UN1114, UN1203 (already forbidden), UN1267, UN1268, UN1993, UN3295, and UN3475 (ethanol and petrol mixtures, with more than 10 percent benzene).

However, an alternative way of degassing has to be offered, and the current situation is not feasible. There is currently only one operating degassing station in the Netherlands, where it takes around 8 hours to fully degas a ship (Koop, 2016). Additionally, there might be waiting times of up to 10 hours and sailing time for the detour to the degassing station. This all results in a lot of idle time for a ship, while there are also costs to the degassing itself. Hence, controlled degassing is a costly operation for ships, and ships might opt for uncontrolled degassing since it is faster and more efficient, as it can be done while sailing to the next loading location.

Another problem with a ban on such a scale would be the regulation done by the Inspectie Leefomgeving en Transport (ILT). Regulation is done based on receiving a signal from so-called e-noses (detection devices that can notice differences in the composition of the air). After the signal has been received, inspectors can request specific cargo information and the current location of a ship. The problem is that the e-noses are placed along a minimal part of the Dutch waterways, meaning a structural overview is missing, making the regulation of uncontrolled degassing quite difficult and unreliable.

Furthermore, if a ship is identified by the e-noses to be degassing illegally, inspectors cannot immediately punish that ship. For that, a whole report has to be written, with information on cargo of the past three months, which has to be obtained through the skipper of a ship. This is quite an inefficient and time-consuming process, which is not beneficial for the probability of punishment. The inspectors also mentioned that even when inspectors can prove a ship has been degassing, the fines do not hurt the ship owners or shipping companies. Especially compared to the cost they would have when degassing legally. Hence, there is little deterrent effect coming from the current way of regulation.

4.3. Actor Analysis

Ships: The term ships is an overarching term for the skippers/ship owners sailing the ship, making the decisions, and performing the behavior related to the case. That said, ships are the most important actors, as they are performing degassing, and their compliance behavior is one of the Key Performance Indicators (KPIs). Although there are other actors related to and responsible for illegal degassing, the Inspectie Leefomgeving en Transport (ILT) can only inspect and directly regulate compliance through the ships. Hence, ships will play a critical role in the model.

Inspectors: The inspectors from ILT are responsible for inspecting the ship and writing the report when a ship is proven to have degassed illegally. Inspectors cannot easily board any ship and perform an inspection. First, a ship that has been degassing illegally has to be picked up by E-noses. Only then the inspectors are allowed to board the ship for an inspection. However, they often decide to gather more evidence beforehand, adding more E-nose signals or testimonies from residents to a report. After boarding the ship, they will inspect it and add cargo and GPS information the skipper provides to the report. Then, the report is sent to the public prosecutor, who will determine the punishment. Proving a ship degassed illegally is quite time-consuming and does not always result in actual proof and, therefore actual punishment. So, not every ship that is flagged by E-noses will get inspected.

Shipping companies: The ships are often owned by shipping companies. For these ships that belong to a shipping company, the company accepts offers from clients who want their cargo shipped. The companies can, therefore, decide to take on cargo that either is or is not compatible, forcing a ship to degas or not. However, the client can also request a ship to degas regardless of compatibility. As far as costs go, the cost for legal degassing at a degassing installation is often paid by the shipping shopping company, and they also get a fine when a ship of theirs is caught degassing illegally. Hence, they have reasons to be interested in illegal degassing.

Local residents: As The Netherlands is densely populated, many people live near the waterways. Hence, there is a ban on degassing at certain locations, and a full ban is considered for even more substances. It should be safe to live near a waterway. That is why the residents of those areas can also call the inspection to notify them of ships that are degassing illegally, as some substances can be smelled. This is then taken into the report that the inspectors write up.

E-noses: E-noses are used to notice ships degassing illegally. They can detect differences in the composition of the air, and when a certain substance is found in a large amount, they send a signal to the company Common Invent, which owns the E-noses. Common Invent will collect the data and send an e-mail to the inspectors of the ILT, which can then add the signal to a report. The E-noses work in a network fashion, so more E-noses along a route have to send a signal in order to obtain an estimation of the location of the source. The estimated source location will be compared to the AIS data of ships around that location so a ship can be coupled to the illegal degassing. The problem is that the E-noses are mostly located around Rotterdam and Amsterdam. Anywhere else ships will not be detected when degassing illegally.

4.4. Data

One of the weaknesses of Agent-Based Modeling (ABM) is the need for sufficient data as a basis for the model and to calibrate and validate the model. The data required to model the degassing situation includes parameters like the number of ships traveling regularly in the Netherlands, amount of trips these ships make, estimations on how often ships illegally degas their tanks and legally degas at a degassing station, etc. Furthermore, estimations on future degassing needs are not necessary but can enhance the value of the model. So, to obtain a model that somewhat resembles the current degassing situation in the Netherlands, data has been provided by the ILT. The data can be divided into qualitative data (e.g., interviews with inspectors and other experts) and quantitative data (e.g., travel data from ships).

The qualitative data is mainly gathered by performing unstructured and semi-structured interviews with experts on the subject of degassing while sailing in the Netherlands. These experts include inspectors and data scientists who have been involved in the subject for the past year. The interviews with the inspectors comprised one semi-structured interview and one unstructured interview. In the semi-structured interview, questions were asked regarding their estimations on the illegal and legal degassing in the Netherlands, the e-nose signals they received, and information about the process, severity, and certainty of punishment. The unstructured interview covered the sailing patterns ships deploy when allegedly degassing. The inspector mentioned in this interview that the e-noses do not cover all the waterways, so there will be cases of illegal degassing that go unnoticed. However, also mentioned in the interview were patterns of ships sailing when allegedly degassing illegally to make up for the limited coverage of the e-noses and increase the reliability of the degassing estimations.

These patterns could be studied through Automatic Identification System (AIS) data. AIS data contain information on, among other things, the time, location, and direction of a ship. By analyzing these data, divergent patterns can be recognized. Adding the hits on these divergent patterns to the hits of e-nose signals can enhance the estimation of illegal degassing. However, the inspectors mentioned that there are waterways where ships are not able to perform the divergent patterns and where there are no e-noses present but where they expect illegal degassing to be happening as well. So, the estimation might still be lacking.

Besides the pattern recognition, the AIS data can also be used to estimate the number of tanker ships traveling regularly in the Netherlands, the number of trips they make, how long trips take, etc. The estimates for all these parameters can be found in Appendix B. For an estimation of the volume of necessary degassing in the Netherlands, the report from Koop (2016) is used. Koop (2016) used Informatie- en Volgsysteem (IVS) data together with information on the compatibility of substances to estimate the volume of degassing. IVS data contains information on the cargo of ships, like cargo type and weight, and is collected at certain points along the waterways, like locks and bridges. The estimates can be found in Appendix B and will be used to help calibrate the model.

5 Conceptual Model

Before proceeding to the actual building process of the model, a conceptual model is first considered. Here, the assumptions are made regarding every aspect of the model (e.g., agents, time, maps), and arguments are given for these decisions. The most important aspect of the model is the objective as to why it is being modeled. In Section 5.1, this objective will be discussed. Then, the agents presented in the model are mentioned in Section 5.2, together with their respective images and the other objects. Next, the conceptualization of the TPB-RCT framework is discussed, including the decision on the use of the Perceived Behavioral Control (PBC). Furthermore, the time representation and the geometric representation are discussed in Section 5.5 and Section 5.6. Finally, in Section 5.7, some assumptions are made more explicit and explained in more detail.

5.1. Objective of the model

The main objective of the model is to gain insight into the effect of regulation strategies related to deterrence, focusing on strategies involving certainty and severity of punishment. This will be done in two types of environments. One is where the possibility of legal degassing is heavily limited, as is the case in the current situation. Secondly, an environment where the possibility of legal degassing is sufficient. Another factor is the composition of the population since deterrence measures do not bear the same effect on an individual level, depending on the individual image of compliance. When dividing the population into the three images, Amoral Calculator (AC), Political Citizen (PC), and Organizationally Incompetent (OI), each will react differently on an individual level. However, they can influence each other through a social network, possibly increasing the effectiveness of a regulation strategy. Therefore, the model will attempt to represent the situation of the degassing case in the Netherlands (Chapter 4) by implementing a social network. Then, several regulation strategies concerning deterrence will be tested, influencing some agents individually more than others. However, more interest will be on how the effect of the strategy will move through the population, indirectly affecting the compliance of others through social factors.

Therefore, the Key Performance Indicator (KPI) will be the compliance rates of the agents, meaning the amount of illegal degassing done over the total amount of degassing. This KPI, being the non-compliance rate, will have to be collected for every image to gain insight into the effects on different types of agents. This will also allow the model to explore another aspect of the objective, the exploration of the performance of the TPB-Rational Choice Theory (RCT) framework regarding regulation compliance.

5.2. Agents and Objects

In the model, only two types of agents will be present, the ships and the inspectors, which differs from the number of actors described in Section 4.3. Some of those actors will be represented in different ways, for example, by using an agent as a proxy or by implementing different factors representing the impact of a certain actor. Others are left out as their role is deemed to be of little importance to the regulation strategies. The harbors and degassing stations will be present in the model in the form of objects, as those are used by the agents but are not able to act themselves.

5.2.1. Ships

As mentioned in Section 4.3, the ships are the model's most important actors and agents. The ship-type agents make the decisions to degas legally or illegally, perform the degassing, and are the actors that are inspected and punished when caught if they are non-compliant.

In the model, ships will belong to one of two images described by Kagan and Scholz (1980), namely the Amoral Calculator (AC) and the Political Citizen (PC). The third image, the Organizationally Incompetent (OI), will not be represented in the model. The OI are known for their incompetence when dealing with complex organizations or regulations. This is assumed not to be the case for the degassing problem in the Netherlands. There are no complex organization structures, as there is a single relationship between skippers and shipping companies or an even simpler structure of a single shipowner. The ships are the final decision-makers. Therefore, they are responsible for their behavior and are punished as such, even though inspectors mention that shipping companies might also be punished.

5.2.2. Inspectors

The second type of agent in the model will be the inspector. Aside from being an inspector, the inspector agent will also be a proxy for the E-noses. So, in this case, the inspector will be bound to harbors and can pick up every signal of illegal degassing within its range as an E-nose would do. However, as an inspector would do, not every signaled ship of illegal degassing will be punished. The inspectors have a seemingly small role but play a big part in integrating different regulation strategies into the model. Since the inspectors can be modified to have a higher range of detection, to simulate more effective E-noses, more freedom of movement along waterways, simulating E-nose placements, a higher probability of punishing an offender, simulating a more efficient connection from detection to punishment, etc.

5.2.3. Objects

Besides the agents that are actively performing actions in the environment, the model will also contain objects that are interacted with by the agents. The two objects that will be modeled are the harbors and the degassing stations. The harbors are only used as a location and destination on the grid. Degassing stations, however, also contain a particular capacity and a waiting list whenever that capacity is exceeded. The capacity can be adjusted to see whether an increased capacity leads to more compliance.

5.3. Conceptualization of the TPB-RCT framework

The most important behavior of the ship agents will be decision-making on whether to degas legally or illegally. This will be done based on the combined TPB-RCT framework, as mentioned in Section 3.1. The implementation of the TPB-RCT into the Agent-Based Model (ABM) will be done with two contrasting Multi-Attribute Utility Functions (MAUFs) as shown in Equation 5.1 and Equation 5.2. These functions will be compared to each other to make a decision. Hence, when $U_{legal} > U_{illegal}$ a ship agent will decide to legally degas their tanks, when $U_{legal} < U_{illegal}$ a ship agent will opt for illegal degassing.

$$U_{legal} = w_{eco} * u_{eco} + w_{pn} * u_{pn} + w_{soc} * u_{soc} + w_{pbc} * u_{pbc} \tag{5.1}$$

$$U_{illegal} = w_{eco} * -u_{eco} + w_{pn} * (1 - u_{pn}) + w_{soc} * (1 - u_{soc}) + w_{pbc} * (1 - u_{pbc}) \tag{5.2}$$

Every utility (u) is given a weight (w) that depends on the type of agent, meaning the political citizen will have different weights than the amoral calculator as their priorities would vary. The multi-attribute utility function consists of four attributes: the economic utility (u_{eco}), utility from the personal norm (u_{pn}), social utility (u_{soc}), and utility from the Perceived Behavioral Control (PBC) (u_{pbc}). The PBC will, thus, be combined with the Multi-Attribute Utility Functions according to the *SE ABM* (see Subsection 3.2.2), resulting in an architecture as can be seen in Figure 5.1.

This is because the decision not to comply can have a big impact throughout the model run, and the threshold will either be a random or arbitrarily chosen value. To make the outcome of the model highly dependent on randomness might negate valuable information, while an arbitrary value will not necessarily outperform the current architecture. However, a threshold can add an extra dimension to the model, as the Perceived Behavioral Control right now only addresses the ability to degas legally, whereas the autonomy to degas legally might be better represented with a threshold.

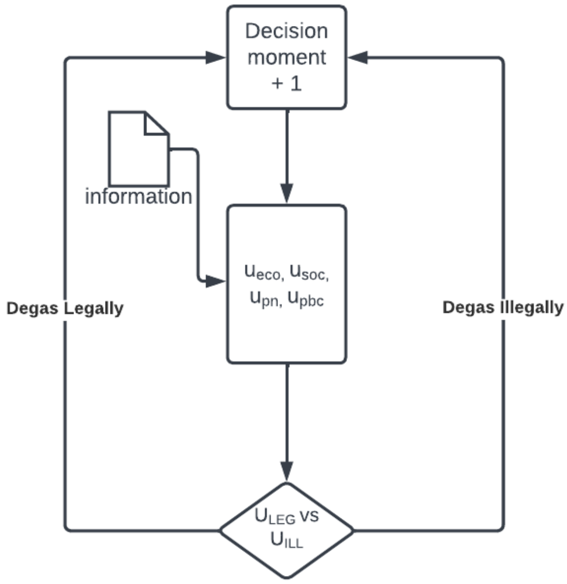


Figure 5.1: Architecture of the Theory of Planned Behavior used in the degassing model

The economic utility will be described following Equation 5.3. C_{F_p} will be the perceived cost of the fine, P_{caught} the perceived probability of being caught, and C_{time} describes the cost of the extra time to degas legally. As P_{caught} will be the perceived probability of being caught, it differs per agent. The fines will become increasingly more expensive when a ship is caught violating the law more often. The perception will be partially due to their own experience, meaning how often a specific agent has illegally degassed and how often it was caught, and partially due to the experiences of their social network (Rincke & Traxler, 2011). Also, it will have a base value as a perceived punishment probability is still experienced even if an agent has never been in contact with punishment, directly or indirectly (Lochner, 2007).

$$u_{eco} = \frac{C_{F_p} * P_{caught} - C_{time}}{C_{time}} \tag{5.3}$$

The utility regarding the personal norm (u_{pn}) will depend on previous personal experience of legal or illegal degassing, as is shown in Equation 5.4. Here, $u_{pn_{i+1}}$ is the new personal norm an agent experiences, u_{pn_i} the current personal norm, $\sum_{d\in S} 1_{\{d=l\}}$ is the sum of the amount of legal degassing the agent has done previously, and $\sum_{d\in F} 1_{\{d=d\}}$ is the total amount of degassing the agent did. To represent a time before the start of the model, the ship agents carry a base value of their personal norm. This base value is then adjusted based on their most recent experience with degassing. To increase the importance of the more recent experiences, the average of all the past experiences weighs as much as the most recent experience.

$$u_{pn_{i+1}} = \begin{cases} \dfrac{u_{pn_i} + \frac{\sum_{d\in S} 1_{\{d=l\}}}{\sum_{d\in S} 1_{\{d=d\}}}}{2}, & \text{if } \sum_{d\in S} 1_{\{d=d\}} \neq 0 \\ u_{pn_i}, & \text{otherwise} \end{cases} \tag{5.4}$$

Similarly to the personal norm, the social utility will be represented by the count of legal or illegal degassing events, divided by the total number of contacts performing degassing in the social network. This is shown in Equation 5.5, where $u_{soc_{i+1}}$ is the new social norm an agent experiences, u_{soc_i} the current social norm, $\sum_{d\in F} 1_{\{d=l\}}$ is the sum of the amount of legal degassing in the social network, and $\sum_{d\in F} 1_{\{d=d\}}$ is the total amount of degassing in the agent's network. Like the personal norm, ship agents will have a base value for the social norm to represent a history of decisions. For the social norm, this base value consists of the average of the personal norms of the ships in an agent's network. Prioritizing recent decisions, the average is taken with the same weight of recent decisions as for the previous social norm.

$$u_{soc_{i+1}} = \begin{cases} \dfrac{u_{soc_i} + \frac{\sum_{d\in F} 1_{\{d=l\}}}{\sum_{d\in F} 1_{\{d=d\}}}}{2}, & \text{if } \sum_{d\in F} 1_{\{d=d\}} \neq 0 \\ u_{soc_i}, & \text{otherwise} \end{cases} \tag{5.5}$$

As for the PBC, a ship agent cannot be asked to spend more time (time representing cost) trying to degas than they would make as a profit legally. Therefore, a cost factor, representing the PBC, is calculated based on the time it costs to degas legally (including time to sail to the degassing station, waiting times at the degassing station, etc.) and the time it would take to degas illegally (the maximum value of the travel time to the next harbor or degassing time). This is shown in Equation 5.6.

$$u_{pbc} = \frac{t_{illegal}}{t_{legal}} \tag{5.6}$$

5.4. Social Network

For the network, there are three major network simulation theories to consider. There is the Erdös-Rényi (ER) model (Erdös & Rényi, 1959), the Watts-Strogatz (WS) model (Watts & Strogatz, 1998), and the Barabási-Albert (BA) model (Barabási & Albert, 1999). The ER model is a completely random graph where every node has a uniform probability p_n of forming an edge with another node. The WS model is a 'small world' network in which neighbors, nodes that are close to each other, have a higher probability of forming an edge. So, a ring of nodes n_n is created, every node forms an edge with a certain amount, k_n, of its nearest neighbors, and then with probability p_n, edges are replaced with new edges towards random nodes. For $p_n = 1$, the WS graph will represent an ER graph. Finally, the BA model is based on a scale-free power law distribution, where a few nodes have a lot of edges and a lot of nodes have a few edges. This network is built by adding nodes n_n, which have to form a certain number of edges m_n, preferentially with high-degree nodes. These are the basics of the respective networks, and there are extensions to each of them that operate slightly differently.

Barabási and Albert (1999) observed that many networks, be it social, business, transportation networks, etc., are built throughout time. Each time a node enters the system, instead of creating edges with random nodes, edges are created with nodes that already possess multiple edges. Nodes with more edges are preferred to attach to for new nodes (Barabási & Albert, 1999). This is unlike the ER model, where nodes are randomly attached to each other, or the WS model, where aside from the neighbors, other nodes are also randomly attached. Besides, the way the Agent-Based Model (ABM) works is that the network will be formed from a list of agents that are generated sequentially. Therefore, the 'small world' network of the WS model is not really suited as most of the Amoral Calculators will form edges with other Amoral Calculators, and the same happens for Political Citizens. Hence, the choice is made for a BA model to represent the social network.

5.5. Time

With the degassing while sailing case, every action takes a certain amount of time. Sailing from Amsterdam to Rotterdam takes approximately 9 hours, degassing a ship's tanks approximately 4-12 hours, etc. Similar actions have to be modeled for the model to represent the real world, with similar time costs. All these actions can influence the decision to degas legally or illegally. For instance, the current location of the ship and the next cargo pick-up location matter when estimating the time costs. Therefore, at least the costs of these actions must be represented in the model to represent reality. However, for a policy to show any long-term effect, of which perception and social effects are a part, the action of deciding on legal or illegal degassing must be performed often, especially when social effects take time to move through the model. This means that for the actual long-term effect of a policy, the model has to run until it represents a few years, which can be very expensive computationally.

Hence, an increment of two hours is chosen for the time step, but only a daytime of 16 hours a day is modeled. Night time is ”skipped” by idling the model for one step. The standard model is run for 100 days, as the degassing behavior changes throughout the year based on the season. The short-term effects are, therefore, studied over approximately one season. The long-term effects are studied over a period of over ten years (4000 days, ten years of 365 days rounded to the nearest thousand). However, these long runs will be done only for specific scenarios as they are computationally expensive.

5.6. Mapping

The agents will interact in a certain environment with each other and the environment itself. It is important for the map to include the necessary elements for both the objective of the model and for the Inspectie Leefomgeving en Transport (ILT). For studying deterrence and compliance, specific locations might be irrelevant and could be replaced by other concepts. However, for the ILT, locations do play a role, for example, when estimating the best positions for degassing stations or when incorporating E-noses. Hence, a map and specific locations will be represented in the model, be it in a simplified manner. In the Netherlands, most of the waterway traffic happens from and towards the harbors of Rotterdam, Amsterdam, and Antwerp (Koop, 2016). Also, estimations of illegal degassing are made based on data from six regions in proximity to these three harbors, and E-noses are only present around Rotterdam and Amsterdam. Hence, the map will only include the locations of these three harbors. Additionally, the current degassing station will be modeled near the port of Rotterdam.

5.7. Additional assumptions

Most parts are based on assumptions throughout the conceptualization phase, as that is how Agent-Based Models (ABMs) are built. However, some assumptions require more explanation, while others have been neglected entirely to this point. Hence, these are elaborated on in this section.

To start, the implementation of the different images, as mentioned by Kagan and Scholz (1980), is already mentioned a few times. However, as this is an important assumption with a possibly significant effect on the outcome of the model, it will be elaborated on once more. It is assumed that the agents in the system are not dealing with complex organizational structures or with complex regulations. This implies that the Organizationally Incompetent (OI) will not be present in the model. This indirectly might cause the model to converge faster, as there is no factor that does not react to either deterrence or personal and social norms. Hence, only the Amoral Calculator (AC) and Political Citizen (PC) will be present in the model. Although the agents will be heterogeneous in the model, the weights assigned to each image will differ by such a margin that there will be no overlap in the preferred decision-making factors. This means that the AC will have minimal interest in the social and personal utility while maximizing its interest in the economic factor. The PC will have the opposite, maximizing personal and social utility while minimizing the economic factor. This might not be a realistic representation of an individual. However, it might enable the isolation of the patterns that will answer the research question and sub-questions.

Another major simplification is the omission of the shipping company in any form. Once again, this is done to isolate the agents' decision-making behavior without other factors beyond their control influencing the outcome. Also, it would result in different modeling choices, extending the model to a point outside the scope of the research. However, it might be an interesting angle to study for the ILT. Hence, a theoretical description of the implementation of shipping companies will be given in Section 9.4 as a starting point for future research for the ILT.

6
Model Formalization

After the conceptualization phase, the model has to be implemented into the code. During this phase, the final details are decided on, like the parameters represented in the model, including their ranges. First, the narrative of the model is presented with the help of a visual representation in the form of a Business Process Model Notation (BPMN). Officially, BPMN models are built horizontally. However, for the sake of readability, a more vertical representation is given in Section 6.1, whereas the official representation is shown in Appendix C. Then, the variables and their ranges are presented in Section 6.2. A visualization of the model is given in Section 6.3. Next, the process for verification is described in Section 6.4. In Section 6.5, the process of calibrating the model is discussed, and the base values for the model parameters are given. Finally, validation is discussed in Section 6.6, implying the lack of validation, the challenges with validating the model, and recommendations to validate the model.

6.1. Narrative

Ship: As mentioned previously, the most essential agents in the model will be the ships. A Business Process Model Notation (BPMN) model of the behavior of a ship is given in Figure 6.1. The main goal of the ship agent is to transport cargo. However, ships might have to degas their tanks after unloading their cargo. In the real world, multiple factors determine if a ship has to degas, for example, the compatibility of the cargo. In the model, this will be done based on a probability factor, which will be estimated from the data. Then, a ship has to decide whether or not to degas legally. If it decides to degas legally, it will sail toward a degassing installation; otherwise, it will sail toward the next harbor to pick up its next cargo, unless the ship is already at the harbor where the cargo is to be picked up, in which case the ship will sail randomly for the time it takes to degas its tanks.

In Figure 6.1, the legal or illegal degassing decision-making process is highlighted with a comment on using the TPB-RCT framework. The TPB-RCT framework will allow for the social norm to be an important factor in the decision-making. The subjective norm that a ship perceives is based on its contacts. The ship will have a list of a random number of other agents from which it can be seen if those agents have been degassing legally or illegally, thereby setting the perceived subjective norm. The attitude related to the TPB will consist of two factors. First, the personal norm for which an agent will look at its personal degassing experiences. Secondly, an economic factor that will weigh the risk of a fine (severity and certainty of punishment) against the extra cost of legal degassing. Finally, the Perceived Behavioral Control (PBC) will be influenced by the possibility to degas legally. A cost that is too high (both in time and monetary value) might not allow a ship to comply with legal degassing. A more detailed description of the conceptualization of these factors and the decision-making behavior is given in Section 5.3.

Inspector: The second agent in the model will be the inspector agent, which is also represented in the BPMN model, see Figure 6.2. The inspector's goal is to regulate the degassing by giving fines to the ships that are illegally degassing. However, an inspector can only give a fine to a ship that has been degassing within the radius of the inspector. Besides the restriction of the radius, an inspector is also incapable of constantly performing inspections. Inspections can only occur a certain amount per week and last a specific time. Finally, an inspector can generally not fine every ship that gets signaled by E-noses. Hence, there is a probability that a ship that is identified to be degassing illegally actually gets punished. All this is to represent the constraints a real-world inspector has.

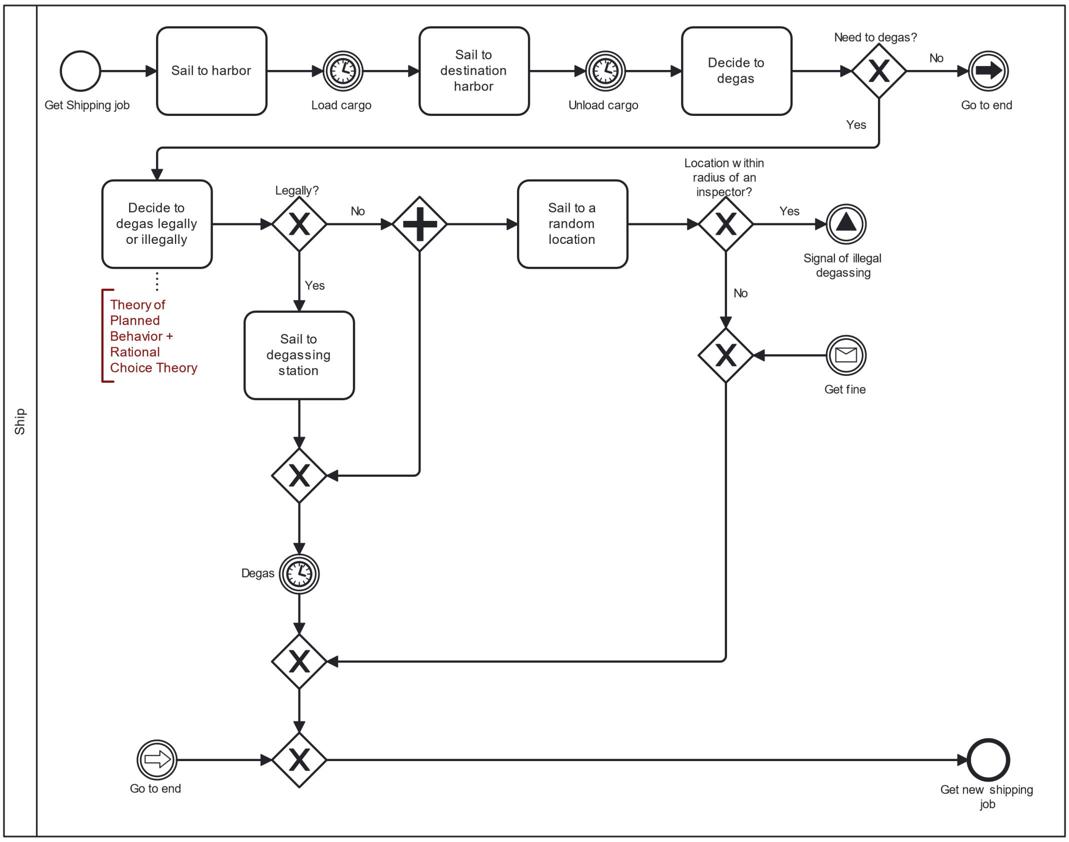


Figure 6.1: BPMN representation of the narrative of the Ship agent

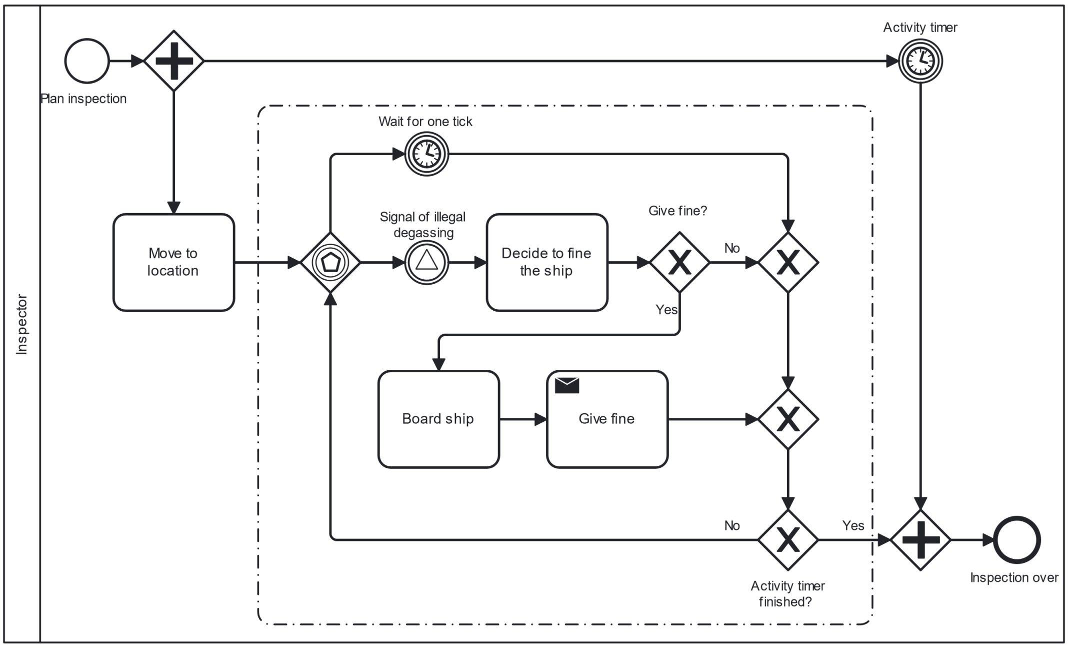


Figure 6.2: BPMN representation of the narrative of the inspector agent

6.2. Variables

The variables that determine the model and agents are shown in Table 6.1, with the according range and description.

Table 6.1: Variables in the model and agents

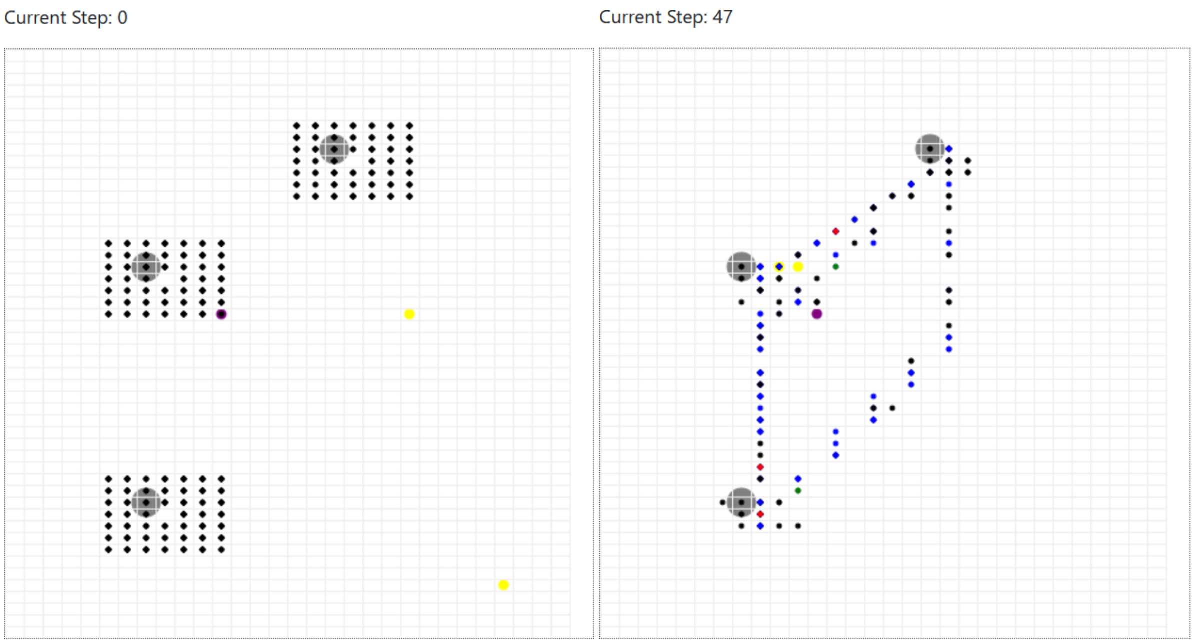
Parameter	Range	Description
Settings		
fines_scaling	$True/False$	Scaling the fines the more often an agent gets punished
amount_of_days	$0-4000$	Amount of days the model will simulate
tick_size	$1-4$	Amount of hours one tick represents
day_hours	$10-18$	Amount of hours is a day
Model Parameters		
num_ships	$700-1400$	The number of ships present in the model
distribution_ac	$0.0-1.0$	The fraction of Amoral Calculators in the population. Fraction of Political Citizens is (1 - distribution\ac)
num_inspec	$0-8$	Number of inspectors present in the model
degassing_probability	$0.015-0.05$	The probability a ship has to degas after unloading its cargo
degassing_stations_amount	$1-3$	The number of degassing stations present in the model.
ds_cost	$0.0-15.0$	The cost related to degassing at a station. Expressed as a time factor in the model.
cost_of_fine	$0.0-160.0$	The cost a ship experiences when it gets a fine. Expressed as a time factor in the model.
punishment_prob	$0.0-1.0$	The probability a ship is punished whenever it gets identified to be illegally degassing.
base_pn_ac	$0.1-0.4$	The personal norm of an Amoral Calculator before the start of the model
base_pn_pc	$0.8-1.0$	The personal norm of a Political Citizen before the start of the model
perception_factor	$1.0-3.0$	Extra factor to the perception of getting caught.
ac_w_eco	$0.7-1.0$	Weight towards the economic utility of the Amoral Calculator
ac_w_soc	$0.01-0.3$	Weight towards the social utility of the Amoral Calculator
ac_w_pn	$0.01-0.3$	Weight towards the personal utility of the Amoral Calculator
ac_w_pbc	$0.01-1.0$	Weight towards the PBC utility of the Amoral Calculator
pc_w_eco	$0.01-0.3$	Weight towards the economic utility of the Policitcal Citizen
pc_w_soc	$0.7-1.0$	Weight towards the social utility of the Policitcal Citizen
pc_w_pn	$0.7-1.0$	Weight towards the personal utility of the Policitcal Citizen
pc_w_pbc	$0.01-1.0$	Weight towards the PBC utility of the Policitcal Citizen
random_seed	$[-\infty, +\infty]$	Random seed to regulate replications of runs
Agent Parameters		
amount_of_trips	$N(29.0, 14.14)$	The number of trips a ship will do in 100 days. Drawn from a normal distribution. Minimum 6.
loading_time	$4-8$	Loading time in hours

Table 6.1: Variables in the model and agents

Parameter	Range	Description
`degassing_time`	$4 - 12$	Degassing time in hours
`inspection_frequency`	$1 - 100$	Number of days between inspections. 1 = daily inspections, 100 = once per run
`activity_time`	$4 - 8$	Amount of hours an inspector is active when inspecting

6.3. Visualization of the model

The visualization of the model is shown in Figure 6.3. In the visualization, the harbors are depicted as large gray circles, the degassing stations as medium-sized purple circles, and the inspectors as medium-sized yellow circles. The ships are depicted as small circles, either black, blue, red, or green, depending on their loading and degassing status, meaning unloaded, loaded, illegally degassing, and legally degassing, respectively. The ships spawn within a specific radius of a harbor as unloaded ships. In the first step, they either switch to loaded or stay unloaded, acquire a destination, and will behave accordingly. Inspectors spawn randomly and will move near a harbor the first time they get active.



(a) Step 0 (b) Step 47

Figure 6.3: Visualization of the initialization phase and running phase of the model

6.4. Verification

An important step in the model is the verification of the model. During this phase, an answer will be sought to the question: did the modeler *"build the thing right"*? (Van Dam et al., 2013, p. 98). Not to be confused with *"did the modeller build the right thing?"* (Van Dam et al., 2013, p. 98), which is a question to be answered through validation of the model, which will be discussed in Section 6.6. For now, it is important to ensure that the model's output is not due to mistakes made during the formalization of the model. Hence, some steps are taken to verify the model. During the building of the model, every separate building block, or so-called unit, was tested the moment it was implemented. This is called unit testing since every small part of the code is tested for its purpose. For instance, the code to calculate the distances was tested by performing the same calculations separately and comparing the outcomes. These unit tests were first performed for a single agent in the model.

However, after all the single-agent unit tests, it is also important to test the interactions between the agents. Hence, many of the same tests were also run for a minimal model and the minimal number of agents to interact: two ship agents and one inspector. For example, tested interactions between agents included changes in the social norm of one agent based on the decision of the other.

Finally, multi-agent tests were performed to see if formalization errors would not be present even on a large scale. For these tests, the model was initialized with different sets of parameters, often at some of the model's limits, so the model's behavior would be predictable. Then, a sanity check was enough to confirm or disprove the working of the model.

6.5. Calibration

In Section 6.2, for the variables, a range of possible values is given. However, for some of the experiments, some model variables will remain constant. To determine their constant value, the model is calibrated on the data acquired from different sources. This implies that these values will represent the current degassing situation. This data can be found in Appendix B, as well as the results from the calibration run. The resulting base values are presented in Table 6.2. The values for the parameters representing the weights have been chosen to make a clear distinction between the Amoral Calculator (AC) and the Political Citizen (PC) in an attempt to isolate the indirect effect of deterrence through social factors. The `distribution_ac`, `degassing_stations_amount`, `cost_of_fine` and `punishment_prob` will be experimented over. The rest of the parameters will be run through a Sobol analysis, which will be explained in more detail in Section 7.2.

Table 6.2: Base values for model parameters

Model Parameter	Base value
num_ships	1050
distribution_ac	0.20
num_inspec	2
degassing_probability	0.0155
degassing_stations_amount	1
ds_cost	6.0
ds_capacity	1
cost_of_fine	40.0
punishment_prob	0.25
base_pn_ac	0.25
base_pn_pc	0.95
perception_factor	1.5
ac_w_eco	0.9
ac_w_soc	0.1
ac_w_pn	0.1
ac_w_pbc	0.4
pc_w_eco	0.1
pc_w_soc	0.9
pc_w_pn	0.9
pc_w_pbc	0.4
random_seed	42

6.6. Validation

The final question still lingering is: *"did the modeller build the right thing?"* (Van Dam et al., 2013, p. 98). To answer this question, the model has to be validated. However, as mentioned in Subsection 3.2.1, one of the weaknesses of Agent-Based Models (ABMs) is the difficulty of validating them. To do that, a significant amount of data is often necessary. For instance, Van Dam et al. (2013) mention historic replay as a method of validation. To perform this kind of validation, a specific real-world scenario is observed and compared with a simulation describing the same scenario to look for corresponding patterns. However, that does imply knowing specifics about, for example, the state of the agents at the start of a scenario, but also knowledge about how they got to that state might be important. What this would mean for the current model is to find a scenario with a specific number of ships, with specific states, and simulate a period with that info. Then, the outcomes of that simulation have to be compared with the outcomes of the real-world scenario. However, even when managing to initiate a simulation that way, the current overview of illegal degassing is not sufficient to compare to the output. Hence, this is not a feasible method to validate the model.

Feasible means of validation include validating the model by comparing it through literature (Van Dam et al., 2013). The problem with using this method for this particular model lies in the ambiguity of the literature. Almost no unambiguous conclusions can be drawn from the literature to compare to the output directly. However, following the literature, there are conclusions for theoretical reactions to deterrence, for example, which can be used as patterns that should at least follow from the model. These patterns can, therefore, be used to validate the model up to some point.

Finally, experts can be used to validate the model (Van Dam et al., 2013). As mentioned in Section 4.4, inspectors were interviewed in a semi-structured way in order to gather data to base the model on. However, from these interviews, it became clear that the knowledge of inspectors is also limited. Hence, no exact measures of, for example, the amount of illegal degassing could be given. This also limits this method's value to validate the model. Still, what can be done is to ask the opinion of inspectors about the state of the current model. However, that will not be done within the scope of the current research.

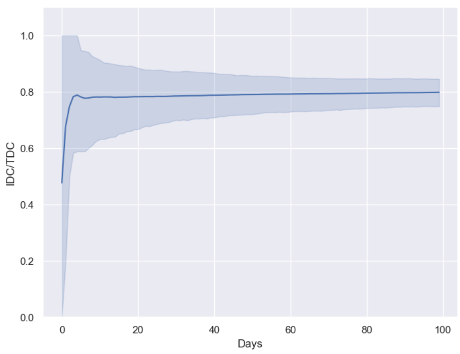
7

Experimental Design

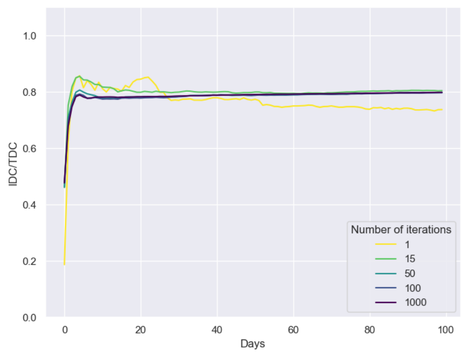
Here, the planned experiments will be described, with an explanation of why these experiments have been performed. First, comparing results between two single repetitions of a run can lead to major errors due to the randomness inherent to the model. Hence, a variability test is described in Section 7.1. Then, a Sobol analysis will be done to verify the influence the model parameters have on the output variable IDC/TDC, which is specified in Section 7.2. Finally, the experiments will be divided into short- and long-term experiments. The short-term experiments are described in Section 7.3 and the long-term experiments in Section 7.4.

7.1. Variability of the model

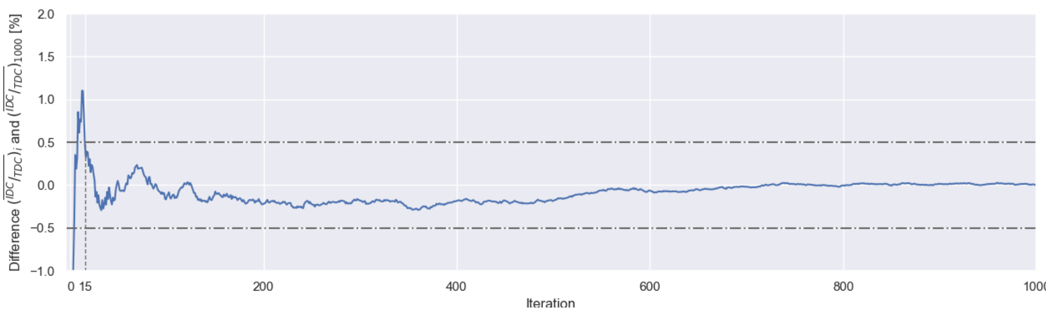
Agent-Based Models (ABMs) are stochastic models that are often built on a certain amount of randomness. A variability analysis is done to gain more reliable results that are not incidental due to the random factors of the model. This will determine how many replications must be performed to get results within an acceptable error margin. For this analysis, the model is run with the base values (Table 6.2) for 1000 iterations. The results are shown in Figure 7.1.



(a) Mean of the outcome of 1000 iterations with the 95% confidence interval.



(b) Mean of the outcomes of runs with a different number of iterations, from 1 - 1000 iterations



(c) Difference between the average outcome at iteration i and the average outcome at iteration 1000

Figure 7.1: Results of the variability tests

As can be seen in Figure 7.1a, the deviation at the beginning of a run is still quite large, being the warm-up period of the model. However, towards the end of the run, the outcomes stabilize, resulting in $(IDC/TDC)_{min} = 0.73$ and $(IDC/TDC)_{max} = 0.81$, which is a maximum variance of 10%. Hence, in 95% of the runs, the outcomes between runs will be within 10%. To get a smaller deviation in outcomes, the model will be run for multiple iterations. In Figure 7.1b, the fluctuations in average outcome per iteration smoothen fast, i.e., the 15 iterations curve already closely follows the 1000 iterations curve, except for the warm-up phase of the run. An argument could be made to run the experiments for 50 iterations, as it follows the 1000 iterations curve more closely throughout the run. However, that means that running an experiment will take more than three times the amount of time, while the outcome at the end of the 100 days is of interest. Following on from that argument, Figure 7.1c shows that from iteration 15 on, the difference between the average outcome until that iteration ($(IDC/TDC)_i$) and the average outcome at 1000 iterations ($(IDC/TDC)_{1000}$) is less than 0.5%. Hence, the experiments will be done over 15 iterations per scenario. However, this means that whenever comparing results within a 0.5% difference, it could be the result of the randomness of the model and, therefore, trivial.

7.2. Sobol analysis

A Sobol analysis will be performed to analyze the model's global sensitivity. Sobol analysis is a variance-based technique to quantitatively measure the input variables' influence on the output variance (Sobol′, 2001; Saltelli, 2002). When dealing with models that contain a high amount of uncertainty, this is an essential step, and Agent-Based Models (ABMs) are within that category due to the assumptions that are made when building an ABM. A global sensitivity will show the influence of the uncertainties in the assumptions, such as a Sobol analysis. The variance of the output caused by the variance of the parameters is explored with the Sobol analysis. This is expressed in Equation 7.1, where V is the variance of the outcome, V_i the first-order contribution of a specific parameter i, V_{ij} is the contribution of the interaction between parameter i and j (Zouhri et al., 2022, p. 10). So, every parameter is tested for its first- and higher-order contribution to the variance of the output.

$$V = \sum_{i=1}^{p} V_i + \sum_{1 \leq i \leq j \leq p}^{p} V_{ij} + \cdots + V_{1 \cdots p} \tag{7.1}$$

The analysis will be performed with the Exploratory Modeling and Analysis (EMA) workbench (Kwakkel, 2017) and the SALib library (Herman & Usher, 2017; Iwanaga et al., 2022). The outcome of this analysis is two-fold. There is the first-order sensitivity index (S_i or S_1), the direct influence of the variance of a parameter on the outcomes of the model. The closer to one this value gets, the more it contributes to the variance of the output. Additionally, the analysis provides a total sensitivity index (S_{T_i}), which includes the influence of the interactions between the specific parameter i and the rest of the parameters. These outcomes are expressed in Equation 7.2 and Equation 7.3 (Zouhri et al., 2022, p. 10).

$$S_i = \frac{V_i}{V} \tag{7.2}$$

$$S_{T_i} = \sum_{k \# i} S_k \tag{7.3}$$

To estimate the contribution the parameters have on the variance of the output, most parameters are varied within their range for a certain number of scenarios while also varying other parameters to get the impact of the interactions on the variance. To get a good estimation of every combination, a sample size of $n_s(2p_s + 2)$ has to be run, where n_s is the number of scenarios and p_s is the number of parameters to be examined. Preferably, all parameters are tested, plus the higher the n_s, the lower the error in the variance results. However, that does require a lot of computational power. Hence, for a computationally manageable set, the parameters in Table 7.1 are set as constants. The weights for the TPB-RCT decision-making implementation are kept constant, although they might impact the variance of the output. This is because the values are chosen so that there is a clear distinction between the two images, not to represent reality, in an attempt to isolate behavior and increase the possibility of observing, for instance, social effects. That leaves 11 parameters to be tested, which will be tested over 100 scenarios.

Table 7.1: Constant variables during the Sobol analysis

Constant variable	Value
num_ships	1050
ac_w_*	*eco = 0.9 *soc = 0.1 *pn = 0.1 *pbc = 0.4
pc_w_*	*eco = 0.1 *soc = 0.9 *pn = 0.9 *pbc = 0.4
random_seed	42

7.3. Short-term run analysis

Where the Sobol analysis will show the contribution to the output variance of certain parameters, it does not show the specific effect of certain variables on the outcome. So, it might show that the cost_of_fine does affect the IDC/TDC by a fair margin, but it will not show the extent of the effect. For instance, there might be little overall variance in the output. Therefore, experiments will be run over the same period of 100 days to gain more insight into the extent of the direct influence of the deterrence measures. The variables that will be experimented with are shown in Table 7.2, and the other variables will remain constant as in Table 6.2, with the only exception being the degassing probability.

To increase the value of the experiments for the Inspectie Leefomgeving en Transport (ILT) and to force agents to make the decision to degas legally or illegally more often, the degassing probability will be raised from the base value. When looking at the ban next year, six more substances (UN1114, UN1267, UN1268, UN1993, UN3295, and UN3475) are included. This will most likely result in more degassing. In Appendix B, estimates of the necessity to degas these substances are mentioned. Adding these estimates to the current amount of degassing done by the base value of the model will shift the degassing probability to degassing_probability $= 0.05$. Hence, this value will be used for both the short-term and long-term experiments.

Table 7.2: Short-term run variable list

Variable	Experiment Values
degassing_station_amount	[1, 3]
distribution_ac	[0, 0.2, 0.4, 0.6, 0.8, 1]
cost_of_fine	[0, 160] in 17 Steps
punishment_prob	[0, 1] in 21 Steps

Increments of the base values of cost_of_fine and punishment_prob are used to experiment with in order to be able to compare the two with regard to the effectiveness of the regulation measure. The maximum value for both will be quadruple the base value.

7.4. Long-term run analysis

The model initially runs over a period of 100 days. However, that only shows the effects of the tested policies on a short-term basis, while for the social side of the model to gain some traction, the decision-making has to be performed a lot more often. The problem is that to simulate multiple years is computationally very expensive to the point that it is not feasible to perform. Therefore, two of the deterrent measures (fine cost and punishment probability) will be run over the course of 4,000 days to better understand these variables' influence in the long run. As there are still computational limitations, a few scenarios will be tested.

First of all, the different environments will be present again, the One Degassing Station (1DS) and Three Degassing Stations (3DS) environments. Secondly, five different distributions between Amoral Calculator and Political Citizen will be tested to gain insight into the effect of deterrence on different population compositions. Finally, the fine cost and punishment probability will be tested separately, in five steps each, to see their individual influence.

Table 7.3: Variables that will be iterated over in the long run tests

Variable	Experiment Values
`degassing_station_amount`	[1, 3]
`distribution_ac`	[0, 0.2, 0.5, 0.8, 1]
`fine_cost`	[0, 40, 80, 120, 160]
`punishment_prob`	[0, 0.25, 0.5, 0.75, 1]

8 Results

In this chapter, the outcomes following the conducted experiments will be discussed. An interpretation of the results will be presented, along with some corresponding conclusions. Also, contributing factors to these outcomes will be discussed, together with the implications drawn from these findings. First, the Sobol analysis will be discussed in Section 8.1. Next, the results from the short-term experiments will be discussed in Section 8.2 to explore the direct impact of deterrence. Then, the findings for the long-term experiments will be elaborated on to explore the indirect effects of deterrence in Section 8.3. Finally, a summary of the results is given in Section 8.4

8.1. Results of the Sobol analysis

In Table 8.1, the numerical representation of the Sobol analysis is shown, whereas the visual representation is shown in Figure 8.1. As can be seen, the variance of the `cost_of_fine` and the `punishment_prob` contribute largely to the output variance. This is true for the first-order ($S1$) and total sensitivity index (ST). The `cost_of_fine` does have a larger contribution, especially considering $ST = 0.46$, which can be explained by the increasing fines the more often a ship agent is punished, making it highly susceptible to variance in, for example, the punishment probability. Furthermore, the `degassing_stations_amount` is also causing a considerable variance, both $S1 = 0.13$ and $ST = 0.16$. On the other hand, the capacity of the degassing stations does not contribute in any major regard, meaning that the location mostly influences the decision to degas legally or illegally, at least in the model. Also, the costs for degassing at a degassing station are quite influential, represented by `ds_cost`. The `ds_cost` can be considered the counterpart of the `cost_of_fine`, the cost to degas legally and the cost to degas illegally, respectively. However, the cost to degas illegally is also related to the probability of punishment, whereas the `ds_cost` is independent in determining the cost to degas legally.

Other noteworthy parameters are the `distribution_ac` and the `degassing_probability`. The composition of the population, which is expressed by the `distribution_ac`, has a relatively small influence on the variance of the output, although it ranges from a composition with only Amoral Calculators (ACs) to a composition with only Political Citizens (PCs), which themselves differ majorly in their utility weights. Still, little contribution is found for at least the short term over which the Sobol analysis is run, meaning that the initial deterrence effect is similar for both images. The `degassing_probability` is interesting as its first-order contribution is fairly low at $S1 = 0.02$, while its total sensitivity is triple that value at $ST = 0.06$. So, more degassing does not necessarily lead to less compliance on its own. However, other factors can strongly add to its contribution, for instance, the number of degassing stations or the capacity.

Table 8.1: Outcomes of the Sobol analysis

Parameter	S1	ST
`cost_of_fine`	0.33	0.46
`punishment_prob`	0.22	0.27
`degassing_stations_amount`	0.13	0.16
`ds_cost`	0.07	0.12
`perception_factor`	0.04	0.08
`degassing_probability`	0.02	0.06

Table 8.1: Outcomes of the Sobol analysis

Parameter	S1	ST
base_pn_pc	0.05	0.05
distribution_ac	0.04	0.04
ds_capacity	0.003	0.005
num_inspec	−0.00007	0.004
base_pn_ac	−0.003	0.0003

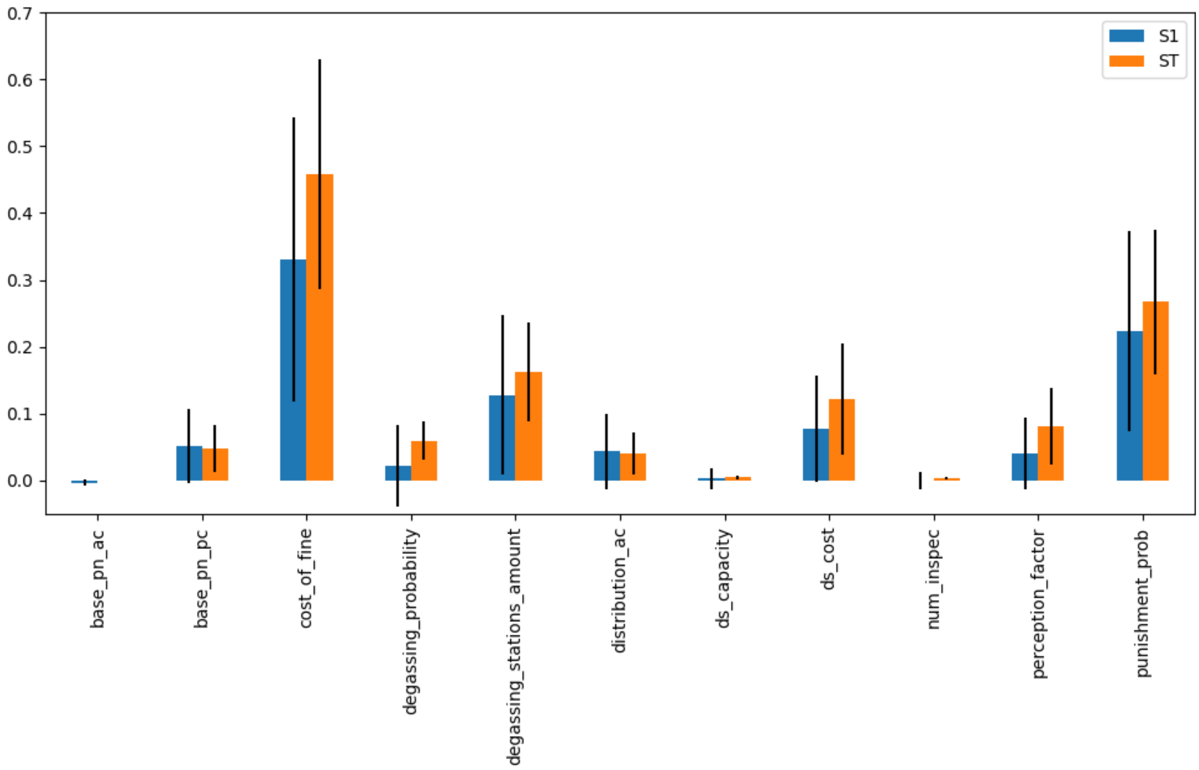


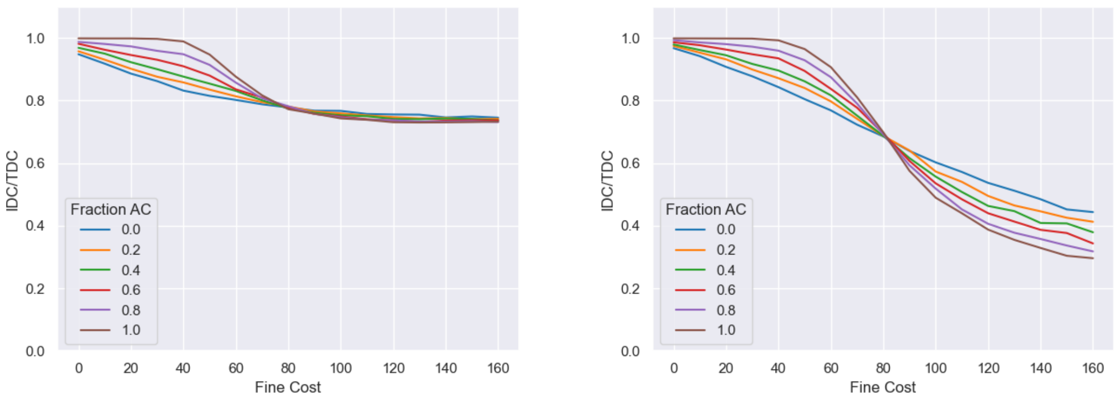
Figure 8.1: Visualization of the Sobol analysis results

8.2. Results of the short-term runs

For the short-term runs, the results for the variation in fine costs are shown in Figure 8.2. There are two scenarios, the One Degassing Station (1DS) scenario and the Three Degassing Stations (3DS) scenario, Figure 8.2a and Figure 8.2b respectively. The relation between IDC/TDC and the cost of the fine is generally not linear but shaped as an S-curve. This means that the influence of the fine costs is low at the start, increases to a maximum, and decreases again until it levels at a limit value.

The composition of the population does not heavily influence the outcome of the experiments. However, it does influence the shape of curves. For the highest fraction of Amoral Calculators (ACs), there is a strong S-shape with a steep decline in IDC/TDC once the fine cost gains traction within the population. The closer the fraction of AC gets to 1, the higher the fine has to be to start affecting the IDC/TDC. However, the lower the fraction becomes, the weaker the S-shape becomes up to a point for the lowest AC fractions, where the curve gradually declines over the full range of the cost of the fine. This results in an almost linear behavior for the 3DS case, see Figure 8.2b. What can also be observed from these results is that the Political Citizens (PCs) are inherently more inclined to comply in the short term, as their compliance rates are higher for lower fines. However, when increasing the fines, at some point, the populations with more ACs will show lower non-compliance. From $(IDC/TDC)_{1DS} = 0.78$ and $(IDC/TDC)_{3DS} = 0.68$ this is the case. This implies that the ACs are generally less inclined to comply than PCs but that they are also more sensitive to the increase in severity of punishment.

It is peculiar that for the higher fines, a limit seems to be met around $IDC/TDC = 0.73$ for the 1DS scenario (Figure 8.2a). For the 3DS scenario, no limit is present for the given range. However, the non-compliance rate in the 3DS scenario ends much lower at around $IDC/TDC = 0.30$ (Figure 8.2b). So, there is a big difference between the two scenarios at high fine costs. The difference between the two scenarios becomes more evident when the 1DS scenario reaches the limit. However, even before that, increasing the severity of punishment has already shown to be more effective in the 3DS scenario, for example, when comparing the moment the compliance rate turns in favor of the ACs.

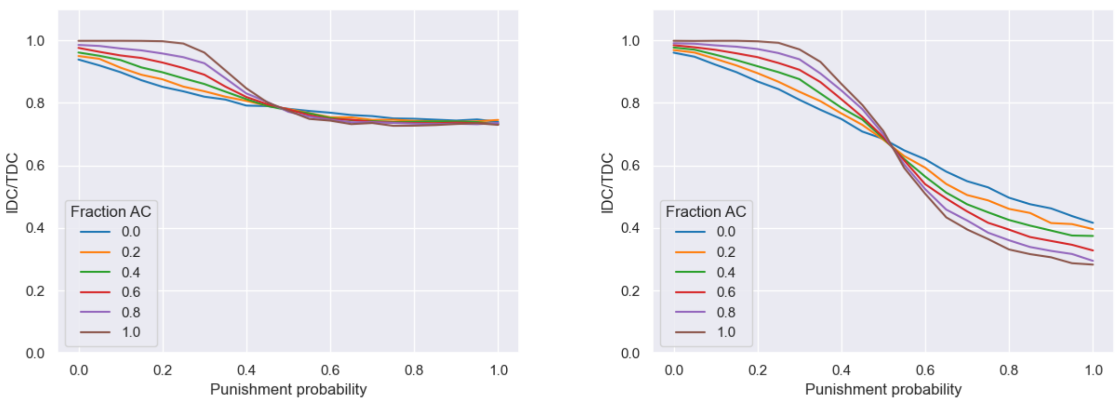


(a) One degassing station

(b) Three degassing stations

Figure 8.2: Fraction of illegal degassing as a function of cost of fine for the short term. Values are shown for day 100, with other variables assigned their base scenario values.

The same experiment has been done for the other deterrence measure, the punishment probability. This is shown in Figure 8.3, where the 1DS scenario is visualized in Figure 8.3a and the 3DS scenario in Figure 8.3b. Both graphs are similar to the results from the fine-cost experiment. Both follow an S-curve, the plots in Figure 8.3a reach a limit at $(IDC/TDC)_{1DS} = 0.73$, and at $(IDC/TDC)_{1DS} = 0.78$ and $(IDC/TDC)_{3DS} = 0.67$ the plots, representing different populations compositions, intersect, which is all similar to the fine-cost experiment.



(a) One degassing station

(b) Three degassing stations

Figure 8.3: Fraction of illegal degassing as a function of the punishment probability for the short term. Values are shown for day 100, with other variables assigned their base scenario values.

Both the short-term experiments show similar results. Interestingly, both the fine-cost experiment and the punishment-probability experiment show a limit at $(IDC/TDC)_{1DS} = 0.73$ for the 1DS scenario. This implies that there is probably a maximum compliance rate that is achievable for the current 1DS situation, which is at some point independent of the severity or certainty of punishment. Furthermore, in both experiments, the 3DS scenario shows a greater effect from the deterrence measures than the 1DS scenario, although this effect is stronger the more severe or certain the punishment is, while for the lower deterrence measures little difference is found between the two cases.

8.3. Results of the long-term runs

For the social and personal effects to become potentially apparent, the model has to be run over a longer period so the agents go through the decision-making process more often, strengthening the social norm and the personal norm.

8.3.1. General Effect of the Environment

First, Figure 8.4 shows the difference between an environment that represents a situation that is difficult to comply with, the One Degassing Station (1DS) scenario, and a situation that makes it easier to comply with, the Three Degassing Stations (3DS) scenario. Unexpectedly, the 3DS scenario results in an even if not marginally higher non-compliance rate, whereas a lower non-compliance rate was to be expected. Hence, additional opportunities for ships to degas their tanks legally do not seem to positively affect compliance for a situation where degassing will occur more frequently.

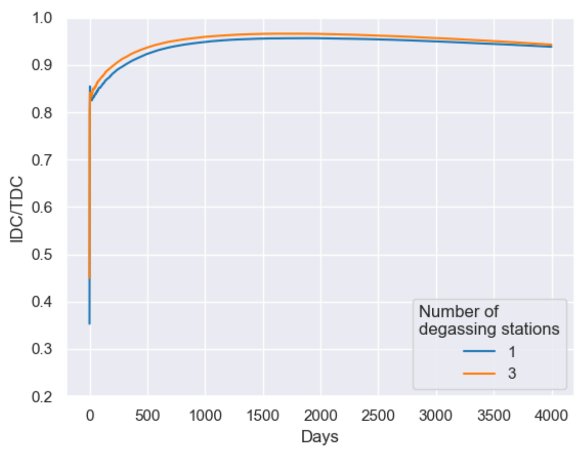
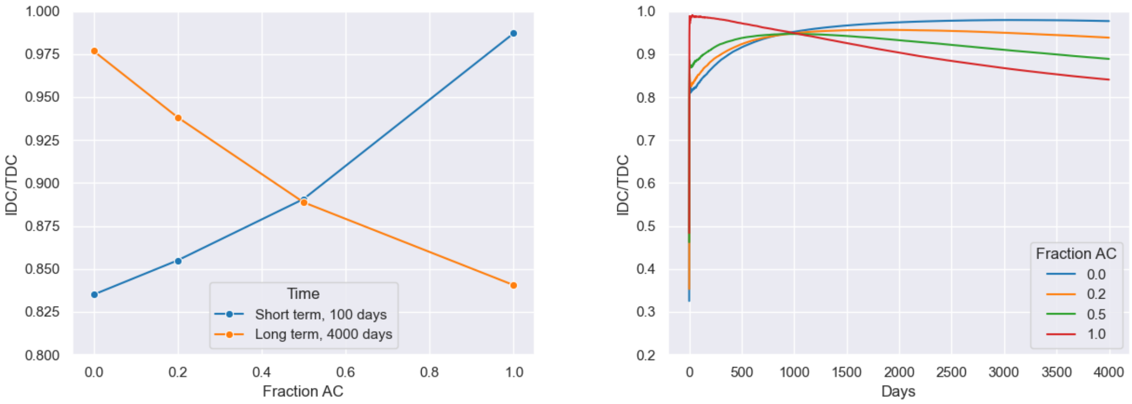


Figure 8.4: Fraction of illegal degassing over time for the scenarios with 1 and 3 degassing stations for the base values.

8.3.2. General Effect of the Population Composition

Secondly, the impact of different fractions of Amoral Calculators (ACs) is researched. The results are shown in Figure 8.5a and Figure 8.6a. Interestingly, in the short term, the higher the fraction of ACs in the population, the higher the non-compliance rates, which holds for both cases. However, when considering long-term runs, it is the opposite. The more ACs, the lower the percentage of illegal degassing. When looking at Figure 8.5b and Figure 8.6b at some point, the plots will reverse, from where on the lower fraction of ACs will result in a lower illegal degassing percentage. This can be explained by the fact that the fines will scale infinitely, so, at some point, an Amoral Calculator will not find it beneficial enough to keep violating the law. That same point for political citizens will be later in the run, as they are more influenced by social and personal norms, and the time for the social norm or personal norm to change or for the fine to matter to political citizens is apparently significantly longer. Hence, the slightly unexpected result.

Also, for both the 1DS and the 3DS case, the population with only ACs is almost fully non-compliant at the early stages of the run. Whereas the other population compositions first show a little compliance,

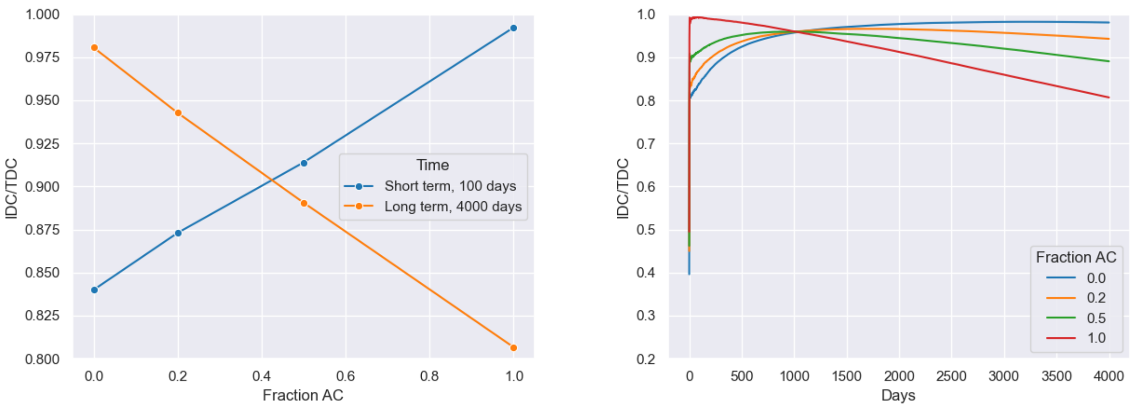


(a) Fraction of illegal degassing as a function of the fraction of Amoral Calculators (ACs) with respect to the total population.

(b) Fraction of illegal degassing in time, for various fractions of Amoral Calculators (ACs) with respect to the total population.

Figure 8.5: Dependence of the illegal degassing on the fraction of amoral calculators in the population for the scenario with One Degassing Station (1DS).

which then slowly declines until the point where the AC finds no benefit in being non-compliant, as discussed earlier. The difference between the two scenarios is that for the 1DS scenario, the curves seem to converge toward the end of the run, whereas the 3DS curves seem to diverge still and accelerate toward lower non-compliance rates. This results in a $(IDC/TDC)_{3DS} = 0.80$, which is 5% lower than the $(IDC/TDC)_{1DS} = 0.84$ for the maximum fraction of ACs.



(a) Fraction of illegal degassing as a function of the fraction of Amoral Calculators (ACs) with respect to the total population.

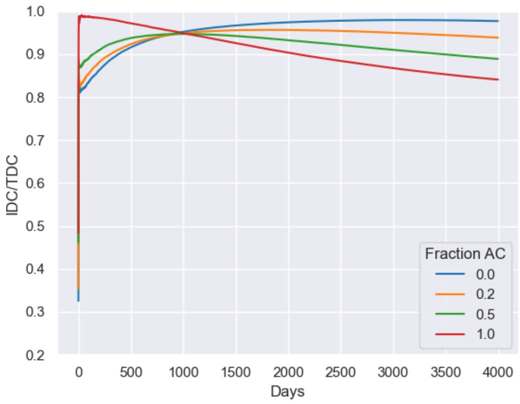
(b) Fraction of illegal degassing in time, for various fractions of ACs with respect to the total population.

Figure 8.6: Dependence of the illegal degassing on the fraction of amoral calculators in the population for the scenario with 3DS.

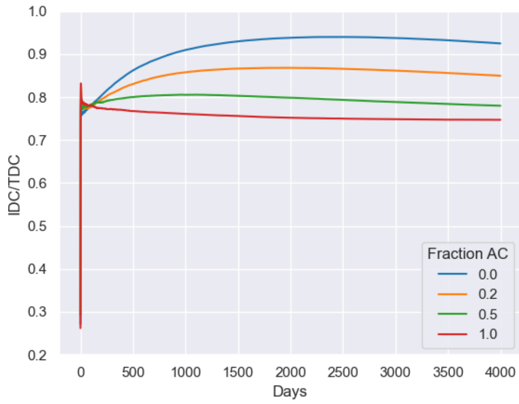
8.3.3. Results of Increasing Severity of Punishment

The results of increasing severity of punishment are shown in Figure 8.7 and Figure 8.8, respectively, for the 1DS and 3DS case. For both cases, the scenario with the base value for the fine and the scenarios for twice and quadruple the base value are shown. Other results can be found in Appendix A. The first salient remark for the 1DS case is the convergence toward a non-compliance rate around $IDC/TDC = 0.73$, as is shown for the $C_F = 80$ when *Fraction AC* $= 1$ (Figure 8.7b), and for $C_F = 160$ when *Fraction AC* ≥ 0.5 (Figure 8.7c). Even when the fines are increased either through policy measure (from $C_F = 80$ to $C_F = 160$) or through an increase every time an agent is punished, the non-compliance rates do not decrease further than $IDC/TDC = 0.734$ (for $C_F = 160$). The limit is, therefore, independent of the severity of the punishment. A possible explanation can be that there is a certain level of compliance that the capacity of the degassing station can handle, after which the waiting times exceed the benefit of not getting a fine.

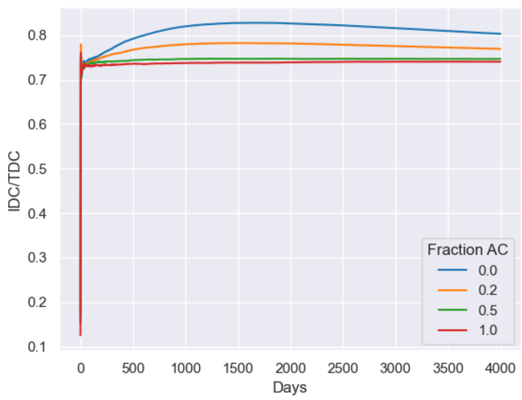
Increasing the severity of punishment in the 1DS scenario does not lead to an ever-increasing compliance rate, or decreasing non-compliance rate as Figure 8.7 shows. However, it does increase the convergence rates at which the curves reach the limit. When comparing the graphs of $C_F = 80$ (Figure 8.7b) and $C_F = 160$ (Figure 8.7c) again, the difference between the non-compliance rate limits $(IDC/TDC)_{C_F=80} = 0.747$ and $(IDC/TDC)_{C_F=160} = 0.734$ is not significant. However, the plots for $C_F = 160$ converge way faster, leading overall to lower non-compliance rates throughout the run.



(a) Base scenario: $C_F = 40$



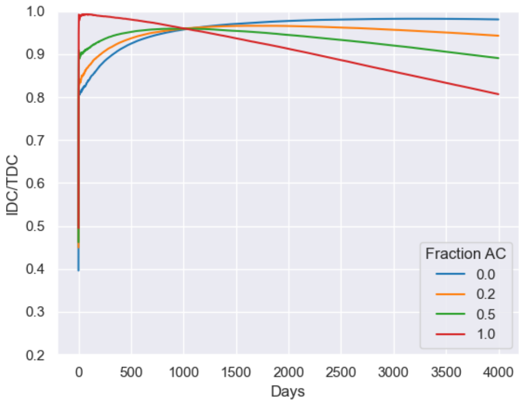
(b) $C_F = 80$



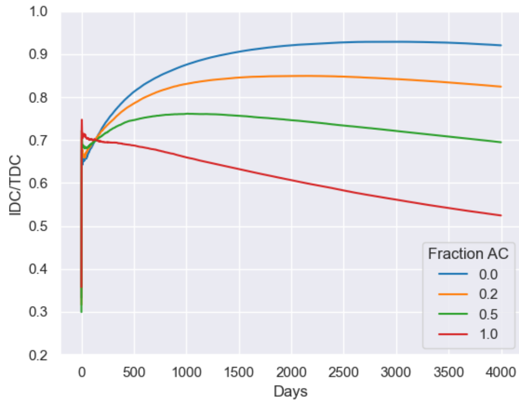
(c) $C_F = 160$

Figure 8.7: One Degassing Station (1DS): Fraction of illegal degassing in time for different fines.

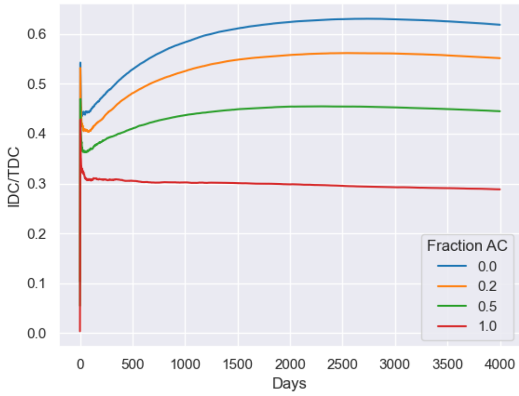
The 3DS case shows similar patterns to the 1DS case for the lower fractions of ACs (*Fraction AC* ≤ 0.2) and the lower fines ($C_F \leq 80$). Furthermore, the 3DS case eventually converges to a limit, after which the non-compliance rate cannot get any lower. The difference is that the limit for the 3DS case is significantly lower at $IDC/TDC = 0.289$. Hence, other distinctions are found in the higher fractions of Amoral Calculator (*Fraction AC* ≥ 0.5) and especially for the higher fines $C_F = 160$ (and $C_F = 120$, Appendix B), as those scenarios pass the limit present for the 1DS case. Another effect of the lower limit of non-compliance is that the plots seem to converge less quickly, if they converge at all. When looking at the $C_F = 160$ scenario in Figure 8.8c, the plot *Fraction AC* $= 0.5$ completes the run at an $IDC/TDC = 0.446$, which is significantly higher than the non-compliance rate for the maximum amount of ACs. While for the same population compositions in the 1DS case, the outcomes were very comparable (Figure 8.7c). Hence, the addition of legal degassing opportunities does increase the effectiveness of the severity of punishment, especially when considering a population more sensitive to deterrence (higher fractions of Amoral Calculators).



(a) Base scenario, $C_F = 40$



(b) $C_F = 80$



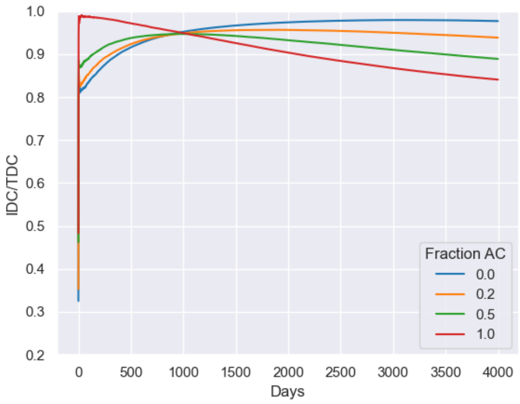
(c) $C_F = 160$

Figure 8.8: Three Degassing Stations (3DS): Fraction of illegal degassing in time for different fines.

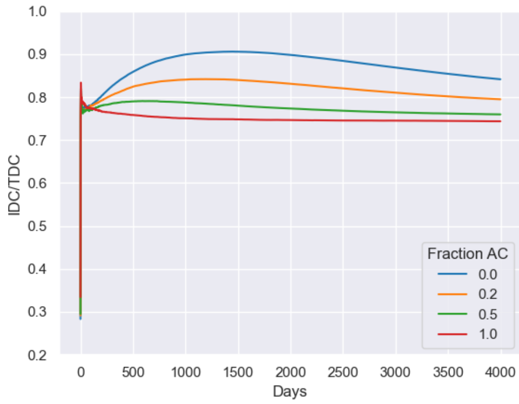
8.3.4. Results of Increasing Certainty of Punishment

For the increasing certainty of punishment, the results for the 1DS case are shown in Figure 8.9 and for the 3DS case in Figure 8.10. First, discussing the 1DS case, the same pattern occurs as for the severity of punishment. Again, a limit is met at around $IDC/TDC = 0.73$. To be more precise, the curve for $P_{punish} = 0.5$ (Figure 8.9b) shows a minimum value of $IDC/TDC = 0.745$, and $P_{punish} = 1$ (Figure 8.9c) settles at a value of $IDC/TDC = 0.733$. Both do not show a difference that is considered significant to their C_F counterparts ($C_F = 80$ and $C_F = 160$, respectively). However, a difference can be observed toward the end of the run for $P_{punish} = 1$ and *Fraction AC* $= 1$. Here, the curve seems to slowly break the limit where it settled earlier, ending at $IDC/TDC = 0.724$. This is a difference between the settled value $IDC/TDC = 0.733$ of 1.24%. Although this might not seem as much, it cannot be dismissed as simply a randomness error of the model, as explained in Section 7.1. An explanation for this pattern can be that, at some point, the agents are caught so frequently that the punishment for the next offense is no longer considered beneficial. The agents might, therefore, start complying again. Furthermore, the plots appear to converge faster than was the case for the severity of punishment, which could be because of a higher effectiveness of increasing the certainty of punishment.

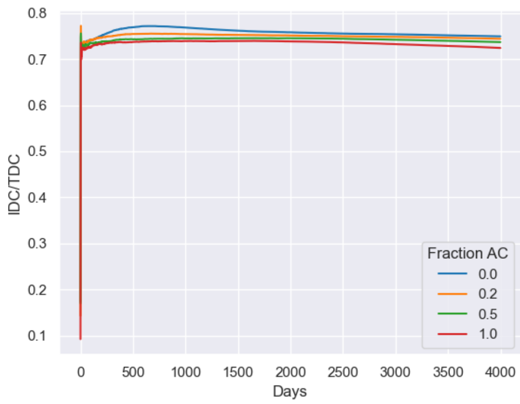
For the 3DS case, similar conclusions can be drawn when comparing the certainty and severity of punishment. The limit that was found in the 1DS scenario is ignored by the plots for the 3DS scenario, as can be seen in Figure 8.10b and Figure 8.10c. However, where the $C_F = 160$ for the 3DS scenario gave the impression of leveling at a limit of $IDC/TDC = 0.289$, the curve of $P_{punish} = 1$ does not level out at all, hence reaching no limit and ending at $IDC/TDC = 0.248$, which is significantly lower than for the severity of punishment. Also, the curves when increasing the certainty of punishment (Figure 8.10b



(a) Base scenario: $P_{punish} = 0.25$



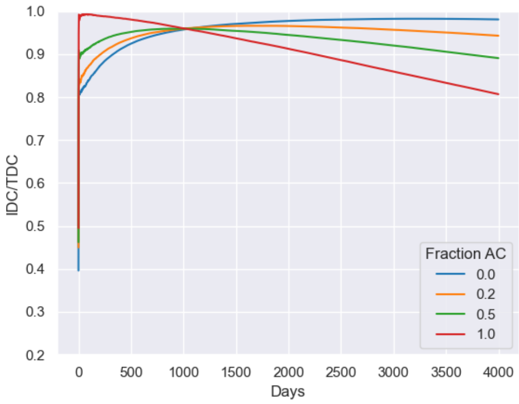
(b) $P_{punish} = 0.5$



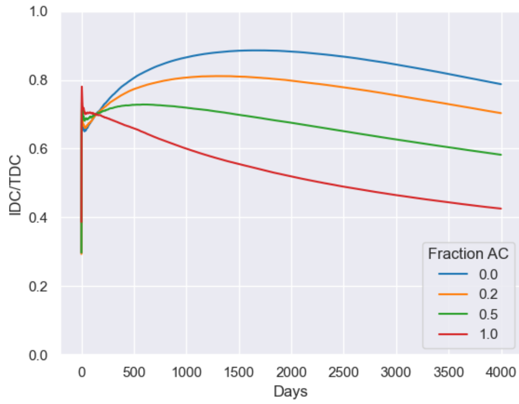
(c) $P_{punish} = 1$

Figure 8.9: Fraction of illegal degassing in time, for different probabilities of punishment. One Degassing Station (1DS).

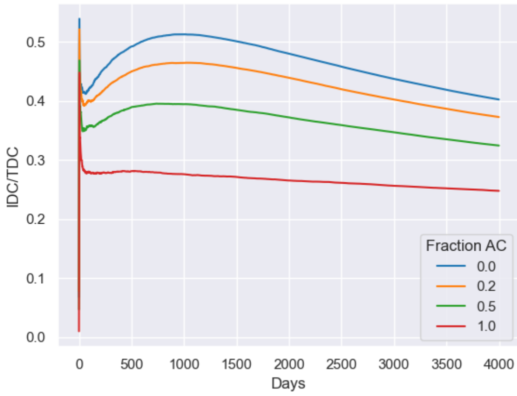
and Figure 8.10c) follow a different pattern than their C_F counterparts, resulting in overall compliance rates that are higher for when increasing the certainty of punishment. Hence, according to the model, the certainty of punishment is a more effective deterrent than the severity of punishment.



(a) Base scenario, $P_{punish} = 0.25$



(b) $P_{punish} = 0.5$



(c) $P_{punish} = 1$

Figure 8.10: Fraction of illegal degassing over time, for different probabilities of punishment. Three Degassing Stations (3DS).

8.3.5. Fraction of Illegal Degassing per Image

As was already clear from earlier results is that ACs are sensitive to deterrence while the Political Citizens (PCs) are not. However, the question that still holds is if the sensitivity of the ACs to deterrence indirectly influences the decision-making of the PCs. To approach an answer to this question, the non-compliance rates of the ACs and the PCs are studied separately. In Figure 8.11, the non-compliance rates for the different images are shown for the 3DS case. What can be observed from the plot is, once again, the confirmation that ACs indeed are strongly influenced by deterrence. Secondly, another sign of capacity issues being the reason for the limits of the compliance rates shown from these graphs is that the populations containing more ACs tend to show a higher non-compliance rate for the ACs. This could imply that once a certain fraction of the population is degassing legally, the waiting times are too long for it to be beneficial, even when deterrence is strong.

Apart from these extensions to earlier statements, the indirect effects of deterrence can also be addressed. When comparing the plots $P_{punish} = 0.25$, $P_{punish} = 0.5$ and $P_{punish} = 1.0$ in Figure 8.11, no difference in pattern is shown for different population compositions for $P_{punish} = 0.25$, for both the non-compliance rates of ACs and PCs. However, for $P_{punish} = 0.5$ the curves already show slight differences in trajectory for the ACs, and with a little delay also for the PCs. What already can be observed for $P_{punish} = 0.5$ is that the ACs for the group with the smallest fraction (*Fraction AC* $= 0.2$) show the lowest non-compliance rates. Accordingly, the PCs also shows the lowest non-compliance rate for the *Fraction AC* $= 0.2$, apart from the population fully comprised of PCs.

The effect gets stronger for the $P_{punish} = 1.0$. Moreover, a difference in the decreasing non-compliance

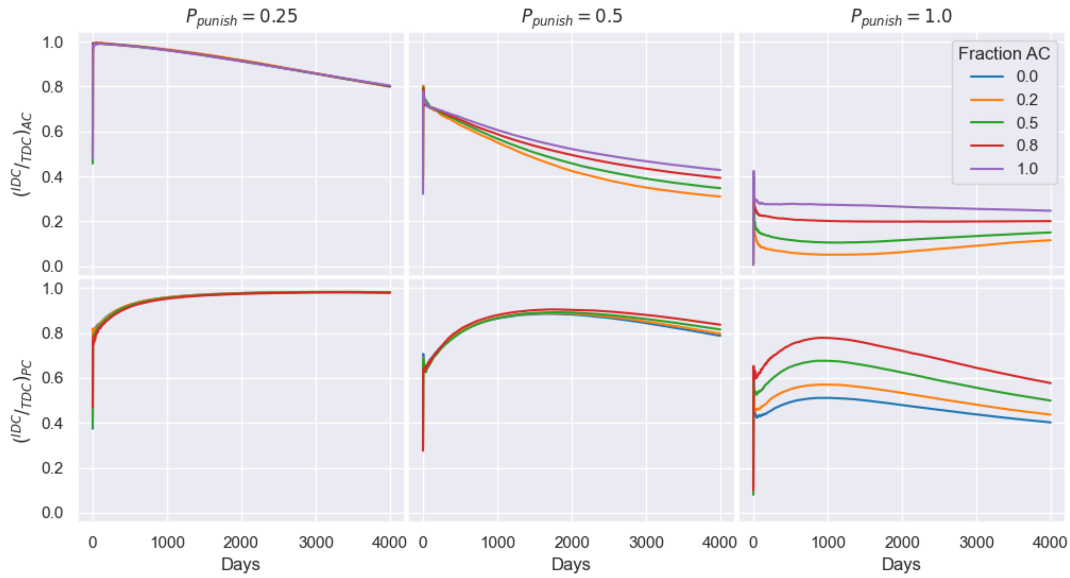


Figure 8.11: Non-compliance rates for the Amoral Calculators (ACs), shown in the upper figures, and the Political Citizens (PCs), shown in the bottom figures. Shown for 3 different punishment probabilities. Three Degassing Stations (3DS).

rate for PCs is found for the different population composition. In the bottom graphs, the *Fraction AC* $= 0.0$ represent a population of only PCs and will therefore present their inherent behavior. When comparing, for instance, the difference between IDC/TDC_{PC} for the *Fraction AC* $= 0.0$ and *Fraction AC* $= 0.8$, it will show the behavior under the influence of a large group that is strongly affected by the deterrence measure in $P_{punish} = 1.0$. The maximum difference found is $\Delta(IDC/TDC_{PC})_{0.0\to0.8} = 0.268$, while the difference at the end is reduced to $\Delta(IDC/TDC_{PC})_{0.0\to0.8} = 0.175$. This amounts to an extra 34.7% decrease in non-compliant behavior, which can be argued to be the cause of the indirect effects of deterrence. However, as this relation is only strongly found for the highest levels of deterrence, no unambiguous conclusion can be drawn from these results.

8.4. Summary of the Results

A numerical representation of the results discussed throughout Chapter 8 is divided into the short-term experiments and the long-term experiments, shown in Table 8.2 and Table 8.3, respectively. From the Sobol analysis (Section 8.1), it became clear that the desired output of the model, IDC/TDC, was mostly affected by the fine cost as the biggest contributor and the punishment probability. Hence, those parameters were experimented with, and these experiments showed a positive effect of deterrence measures. However, more remarkably, for the One Degassing Station (1DS) scenarios, the short-term experiments show a limit of around $IDC/TDC = 0.73$, after which increasing the severity or certainty does not appear to influence the non-compliance rate. The same limit is found for the long-term experiments, as can be seen in Table 8.3. So, apparently, a limited (non)-compliance rate can be reached with the number of degassing stations in the current situation, independent of deterrence measures. The only possible exception to this pattern for the 1DS case could be the scenario with $P_{punish} = 1$ and *Fraction AC* $= 1$. Unlike all the other plots settling at the limit, this experiment shows, after settling at the limit value, to decrease again. This could be due to agents being punished so frequently that it stops being beneficial not to comply.

Another insight that is gained from studying the results is that when changing the environment into a situation that enables compliance, increasing the severity and certainty does have a more prominent effect. Both the experiments, Table 8.2 and Table 8.3, show a positive difference (i.e., less non-compliance) between the 1DS and Three Degassing Stations (3DS) scenario for the scenarios higher than the base values (i.e., $C_F > 40$ and $P_{punish} > 0.25$). The effects are more evident for higher fractions of Amoral

Table 8.2: Summary of the results of the short-term run experiments

			Fraction AC					
			0	**0.2**	**0.4**	**0.6**	**0.8**	**1**
C_F	**40**	**1DS**	0.833	0.857	0.876	0.909	0.948	0.989
		3DS	0.843	0.871	0.896	0.931	0.959	0.992
	80	**1DS**	0.778	0.781	0.774	0.778	0.781	0.772
		3DS	0.685	0.687	0.687	0.694	0.691	0.698
	160	**1DS**	0.745	0.741	0.737	0.736	0.731	0.732
		3DS	0.443	0.412	0.379	0.343	0.318	0.296
P_{punish}	**0.25**	**1DS**	0.837	0.852	0.879	0.911	0.946	0.990
		3DS	0.844	0.868	0.898	0.928	0.959	0.992
	0.5	**1DS**	0.781	0.780	0.776	0.779	0.772	0.775
		3DS	0.685	0.682	0.686	0.691	0.700	0.710
	1	**1DS**	0.739	0.745	0.732	0.732	0.736	0.730
		3DS	0.416	0.396	0.374	0.328	0.295	0.282

Calculators (ACs). However, for the base scenario ($C_F = 40$ and $P_{punish} = 0.25$), no difference or even slightly negative differences are found when adding degassing stations.

Table 8.3: Summary of the results of the long-term experiments

			Fraction AC			
			0	**0.2**	**0.5**	**1.0**
C_F	**40**	**1DS**	0.977	0.938	0.889	0.840
		3DS	0.981	0.943	0.891	0.807
	80	**1DS**	0.925	0.850	0.78	0.747
		3DS	0.920	0.824	0.695	0.524
	160	**1DS**	0.803	0.769	0.747	0.740
		3DS	0.619	0.552	0.445	0.288
P_{punish}	**0.25**	**1DS**	0.977	0.938	0.889	0.840
		3DS	0.981	0.943	0.891	0.807
	0.5	**1DS**	0.841	0.795	0.760	0.743
		3DS	0.788	0.703	0.582	0.426
	1	**1DS**	0.750	0.744	0.737	0.724
		3DS	0.403	0.373	0.325	0.248

Finally, the anticipated indirect impact of deterrence, aimed at influencing a fraction of the population sensitive to deterrence to subsequently impact those less responsive to deterrence but more to social norms, did not occur prominently during the experiments. Only a marginal influence of the social norm is found for extremely high deterrence measures ($P_{punish} = 1.0$). While this does not entirely negate the possible existence of this effect, it does decrease the likelihood, considering its minimal indication even when purposefully isolating the pattern. Hence, under more realistic circumstances, the probability of this pattern occurring is likely even lower, at least within the current model framework. An explanation is the substantial influence of the personal norm on the decision-making process, while the personal norm was easily adjusted to values influencing the outcome across multiple decision-making events. Arguments supporting this result can be found in the literature, where often the personal norm is dominant over the social norm (Grasmick & Bursik, 1990; Wenzel, 2004). Nevertheless, further research might be necessary to address potential ambiguities in these findings.

9
Discussion

The previous chapter provided a detailed presentation of the results, offering some initial insights into the implications of the findings. This chapter takes a more extensive approach in elaborating on these implications, particularly focusing on their significance for the Inspectie Leefomgeving en Transport (ILT), as will be described in Section 9.1. Then, the performance of the model will be discussed in Section 9.2. Section 9.3 will reflect on the limitations of the model, with the insights gained by performing the experiments. The chapter concludes, in Section 9.4, with potential improvements of the model and the framework that could be considered for future research opportunities.

9.1. Implications for the ILT

For the Inspectie Leefomgeving en Transport (ILT), it is important to gain insight into multiple aspects of regulation. Not only are the regulation strategies employed important, but so are the population subject to these regulations and the environment, as this can help or hinder regulation. From the results of the model, Chapter 8, a few things stand out regarding the regulation aspects.

First, the most prominent result is the difference between an environment containing One Degassing Station (1DS) and one containing Three Degassing Stations (3DS). For the 1DS case, there is a limited value after which the non-compliance rate does not appear to decrease any further, independent of the certainty or severity of punishment. The limited value is even independent of the time, while the fines are ever-increasing the more often an agent gets caught for illegal degassing. An explanation for this pattern is found in the number of agents that are degassing legally at some point in time, for which the capacity is insufficient, leading to waiting times that exceed the benefits of not being punished. Adding to this argument, inspecting the non-compliance rates of the Amoral Calculators (ACs) and Political Citizens (PCs) separately, as is done in Subsection 8.3.5, shows the non-compliance rates of the ACs increasing again whenever more PCs start to comply. The effect on the impact of deterrence is major, as for the 3DS case, this limit is easily passed, resulting in better compliance rates and stronger reactions to deterrence. However, for the base values of the model, no difference is found in the variation of the environment. Still, the difference in effects when increasing the certainty and severity of punishment is so substantial that providing sufficient degassing opportunities is vital for regulation. Without enough legal degassing opportunities, there is no way to regulate the illegal degassing of ships.

Next, as was already discussed based on the literature, deterrence does not simply impact every type of actor. As Kagan and Scholz (1980) showed in their study, different images react differently when faced with deterrence. Agents that are more economically driven, ACs, are shown to be more sensitive to increments in severity and certainty of punishment, whereas agents that are more morally driven, PCs, are shown to be significantly less sensitive to deterrence. The results show exactly this behavior. Amoral Calculators show to be more compliant when the severity or certainty of punishment increases. Political Citizens are less affected by these deterrence strategies and will only react accordingly for very high levels of deterrence, which can be questioned to be reasonable in different ways. Still, this behavior does follow the conclusion by Bachman et al. (1992): people with higher moral standards tend to be less impacted by deterrence. These moral standards follow personal and social norms, which might be affected by deterrence indirectly. However, the model shows little evidence of indirect influences of deterrence. Results in Subsection 8.3.5 show the contribution of ACs to the non-compliance rate declining. However, these results show a limited decline in non-compliance for the PCs as a reaction to the declining compliance rate of ACs. So, no unambiguous conclusion can be drawn for the indirect effects of deterrence.

Arguably, this is due to the impact of the personal norm, which, as discussed earlier, might have been too sensitive to early non-compliance. However, the literature also states that the personal norm is often of greater influence than the social norm (Wenzel, 2004), raising the question of whether increasing the robustness of the personal norm will actually lead to an occurrence of the indirect effect of deterrence. Furthermore, these results followed an attempt to isolate such behavior. The behavior of the different images has been exaggerated, so the PC should have reacted strongly to changes in the behavior of others. However, even then, this was not the case. So, when a population is modeled more realistically, without these extreme preferences in utility, probably even less effect of the social effects, as currently modeled, will be observed, making them practically non-existent. Hence, targeting the AC image is unlikely to impact the PC image. This means that different images have to be considered, and, therefore, different regulation strategies have to be considered when deciding on the policy to regulate illegal degassing.

9.2. The TPB-RCT framework in an ABM

In some compliance literature, enhancing the Theory of Planned Behavior (TPB) with different factors, for instance, financial risks related to non-compliance, was shown to improve the performance when predicting the intention to comply (Sommestad et al., 2015; Wu et al., 2021). Hence, the choice to enhance the TPB with the Rational Choice Theory (RCT). The TPB was implemented in the Agent-Based Model (ABM) according to an architecture by Schwarz and Ernst (2009), which was called the *SE ABM* by Muelder and Filatova (2018). In this architecture, all the factors determining the intention are combined into a Multi-Attribute Utility Function (MAUF). To integrate the RCT with the TPB, the personal norm was split into an economic factor and a personal moral factor. The Perceived Behavioral Control (PBC) is in this architecture solely part of the MAUF determining the intention of an individual. This can be argued to not be according to the original Theory of Planned Behavior (Ajzen, 1991), as the influence of the PBC also extended toward the actual behavior. However, for this study, the perceived ability to perform compliant behavior was of interest, for which the PBC as part of the utility function was argued to be sufficient. Other decision that could have been made are discussed in Section 9.4.

The requirement to describe multiple heterogeneous actors interacting and influencing each other made Agent-Based Modeling (ABM) a suitable method to explore the combination of these frameworks. The results that came from the experiments done with this model affirm that thought. To differentiate between agents, the theory of Kagan and Scholz (1980) was taken to an extreme, with actors driven almost solely by economic factors and actors almost solely driven by moral factors, both personal and social, representing the Amoral Calculators (ACs) and Political Citizens (PCs), respectively. Throughout the experiments, these different agents behaved exactly as is often described in the literature. Deterrence was mainly effective for the agents following the AC image, while it had relatively little to no effect on the agents following the PC image, aside from extreme cases of deterrence, which can be considered improbable. This is exactly as the literature describes. However, it does not necessarily confirm the performance of the framework, as this behavior is directly implemented in the model. Still, some other aspects also followed the literature without being implemented directly into the model. For instance, the certainty of punishment proved to be more effective than the severity of punishment, something that has been already mentioned in the early stages of deterrence literature (Beccaria, 2006; Becker, 1968). Another aspect is the strong impact of personal norms on the willingness to comply, which, similar to what literature says (Grasmick & Bursik, 1990; Wenzel, 2004), has a stronger impact than the social norm. Similar behavior is observed in the model. When the personal norm is shifted, it is hard for the social norm to make up for that shift, at least for the agents valuing the social and personal the same. the PCs. Hence, there are some aspects that show a positive performance of the TPB-RCT framework in relation to compliance research, at least when combined with Agent-Based Modeling.

However, the greatest value this combined TPB-RCT framework provides is the flexibility of the framework in its use. Although one specific case has been studied during this research, the framework can be adjusted to various other cases by simply altering the interpretation of the different components and adjusting the weights. It does require the case to have a clear economic component that could potentially be a reason for non-compliance. Also, a form of perceived ability to comply can be an important aspect to consider together with its representation in the model, as was the case in the degassing situation.

This does not mean the TPB-RCT framework performs perfectly. There are still some aspects considered to be influential that have not been implemented during this research. Moreover, some aspects might benefit from a different representation than currently is the case. Both the addition of new and modification of current aspects might benefit the performance of the TPB-RCT framework in ABM. However, that is considered out of the scope of this research. Hence, the limitations and possible future improvements of the model and the framework are discussed in Section 9.3 and Section 9.4. Still, the performance of the current implementation of the TPB-RCT framework into an Agent-Based Model can be considered positive.

9.3. Limitations of the model

The biggest limitation of the model lies in the decision-making behavior of the agents. It is simplified into four different factors: the economic, social, personal, and Perceived Behavioral Control (PBC) factors. This approach translates all these factors into rational decision-making, which is necessary when trying to simulate the situation. That might have had little influence on the economic side of the behavior. However, it also required simplifying complex psychological behavior. In the model, that complex psychological behavior was simplified to the point of it being just one parameter. Thereby reducing the robustness of the model.

This was especially the case for the implementation of the personal and social norm for the Political Citizen (PC) image, as this image was heavily skewed towards these psychological factors of behavior. For instance, the personal norm was only influenced by the base value an agent initialized with and the agent's degassing choices. If the agent's first decision were to degas illegally, the base value would be halved. When an agent values the personal norm, half the base value after just one decision could greatly impact the rest of its behavior. The likelihood for the first decision to be degassing illegally was very large as the worst-case scenario was modeled in which the compliance rate was naturally very low. Hence, through the simplification of the personal norm, the impact of one decision might significantly influence the outcome of the model. This can, for example, be why the indirect influences of deterrence did not show as prominently as expected. It takes a big shift in social norms to compensate for the loss in personal norms, which can take a while.

Additionally, the model is calibrated to a scenario that might very well be a worst-case scenario, meaning that the non-compliance rates are relatively high. For Political Citizens to also follow the calibrated scenario, there is a relatively high probability that they will not comply the first time they have to make a decision, which will instantly shift their personal norm. This will influence their behavior throughout the rest of the run, making them less sensitive to changes in social norms. Hence, a scenario where the initial compliance rates are higher might yield different results.

The final simplification that might influence the output is the simplification of the punishment. As it is now, inspections are modeled as a simple counter that only shows the effect the next time an agent decides to comply. For the next decision, the fine is perceived to be higher, and a different perception of the certainty of punishment is acquired. The ever-increasing fines result in a situation where it is eventually not feasible to degas illegally. However, the non-compliance rates never went to zero. so changing that aspect will not necessarily enhance the performance of the model. However, what might be forgotten is the social and personal aspects of being punished for illegal behavior. As is mentioned in, for instance, Grasmick and Bursik (1990), a personal factor like shame does play an important role in the effect of being caught, more than the actual punishment. This is not represented in the model, while it can have a major effect on agents that act as Political Citizens.

9.4. Recommendations for Future Research

As is often the case when doing research, when trying to explore certain questions and solutions, other questions and solutions will emerge. Hence, opportunities for future research are discussed. To be more precise, two future research opportunities will be discussed. The first will explain subsequent research mainly relevant to the Inspectie Leefomgeving en Transport (ILT), but some conceptual remarks might also be useful for extending the RCT-TPB framework. Secondly, suggestions are made that could enhance the value of the current implementation of the RCT-TPB framework for compliance research. The theoretical improvements should be assessed in future research.

First, currently, in the model, the actual presence of shipping companies is ignored. This assumption was made in order to simplify the model. However, in reality, there are shipping companies that have skippers working for them, which denies the skippers full control over their decisions. Shipping companies can, for example, decide whether certain ships have to degas. However, they can also be punished if many ships associated with a certain shipping company appear to be degassing illegally. Furthermore, it is probable that ships related to the same company are in contact with each other.

There are a few changes that could be made to the current model to incorporate shipping companies. First, as was mentioned, skippers associated with a company do not always have full control over the decisions they make. This relates to a form of Perceived Behavioral Control (PBC), namely autonomy, which is mentioned by Sommestad et al. (2015). The possible loss of autonomy could be implemented by an additional component of PBC that acts as a barrier, as was the case for the *RR* and *MF ABMs* (Muelder & Filatova, 2018). So, when a shipping company decides for a ship to degas illegally, the decision of the ship gets overruled. It can also work the other way around, giving the ILT the opportunity to explore regulations that target shipping companies. Also, the social network of the ships can contain mainly contacts that are related to the same shipping company. This could be expressed by using a modified Watts-Strogatz (WS) network (Watts & Strogatz, 1998), where the neighbors are ships from the same company with which edges are certainly formed. Additionally, other ships from outside the company could become part of the network. Hence, by adding the shipping companies in the model, different aspects and strategies might be explored in future research.

Second, the implementation of the TPB-RCT framework into an Agent-Based Model (ABM) has shown some promising results. However, as discussed earlier in Section 9.3, the biggest limitation of the model was the simplification of the psychological aspects of the model (e.g., personal and social norms). This caused a lack of robustness of these parameters, which might have caused the indirect effects of deterrence to be ambiguous. So, the personal norm can be enhanced by making it less sensitive to a single decision and not letting the most recent behavior overwhelm the personal norms that are nurtured from birth. That can be done through different methods. For instance, a constant base personal norm could be incorporated, which will be considered for every new decision, as it is supposed to represent the core value of an agent. Also, the personal norm could be made dependent on the punishments that are received so that punishments would increase the personal norm and, therefore, act as a small reset. This approach would follow the conclusions from Grasmick and Bursik (1990), as they concluded that shame, one's personal guilt, plays a major role in the decision to comply.

Finally, in the current implementation of the RCT-TPB framework, the social norm solely represents what others are perceived to be doing, described by Record (2017) as the descriptive norm. However, the normative norm, what others want me to do (Record, 2017), is not included in the framework. This could be implemented in a similar fashion as the history of an individual's personal norm by giving the social norm a constant base value, which is considered for every decision. These suggestions are expected to make the model more robust and can add value to compliance research as it could show less ambiguous results regarding, for example, the indirect impact of deterrence. Hence, these additions are recommended for future research that will utilize this framework in the context of compliance.

A possible implementation of the adjustments for future research is visualized in Figure 9.1, the changes are reflected through the dotted lines of the components. The personal norm component is split into a static component representing the historic personal morals and values, and a dynamic component, which is variable to personal experiences, like by being caught or by performing (non-)compliant be-

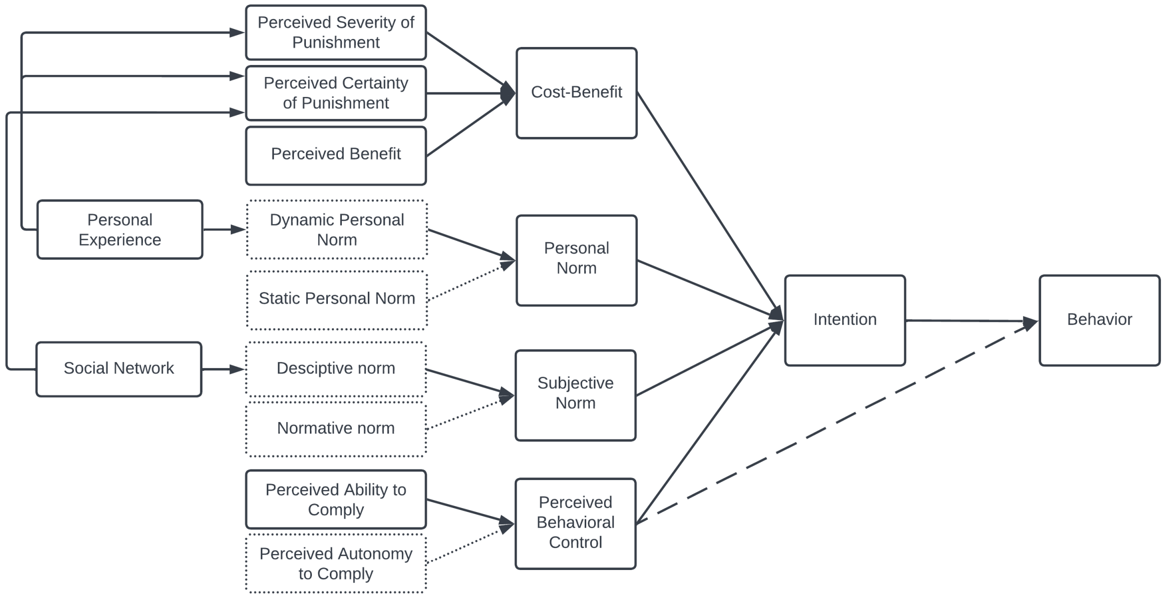


Figure 9.1: Representation of the TPB-RCT framework with the adjustments recommended for future research

havior. Similarly, the social component is separated into a normative norm, which will be static, and a descriptive norm, which will adhere to the behavior of the social network. Finally, the PBC expanded by adding a perceived autonomy component, to represent the autonomous control regarding a decision.

10 Conclusions

To conclude, the literature on compliance, specifically deterrence, shows that deterrence is not a simple concept where increasing the certainty and severity of punishment will automatically result in higher compliance. Many factors will influence the effectiveness of deterrence, and many are psychologically related. For instance, social and personal norms and control factors. To gain insight into the psychological factors, the RCT framework, a theory focusing on the economic side of decision-making, was enhanced with a psychological framework, namely the TPB. Combining these frameworks can represent both the economic side of deterrence and the social and personal side. To explore the effects of deterrence in different cases and the performance of the combined frameworks, an ABM was built for a case study regarding illegal degassing while sailing in the Netherlands. The case study was done in association with the ILT.

For the ABM, different factors have been translated to be used in the model. For instance, the agents represented in the model, the time representation in the model, and the decision-making represented by the combined framework of the TPB and RCT. For the framework, two contradictory Multi-Attribute Utility Functions (MAUFs) were used to express every concept as a utility, in accordance with Muelder and Filatova (2018). A choice was made for the PBC to be only represented in the utility functions instead of as a threshold, resulting in a similar architecture to the *SE ABM* (Schwarz & Ernst, 2009; Muelder & Filatova, 2018). This model is verified and calibrated to a scenario received from estimations through data analysis. However, no validation of the model has been done within the scope of this research.

With the model, a few experiments were run. A variability test showed that the model must be run for at least 15 repetitions to get an error with respect to 1000 repetitions within 0.5%. Then, a Sobol analysis was performed to gain insight into the contribution of different parameters to the variation of the output. From the Sobol runs, the fine cost, punishment probability, and the number of degassing stations were found to be the most influential, and these were then tested for the short-term and long-term experiments.

The short-term experiments were performed to test the initial impact of the different strategies within two different environments, the One Degassing Station (1DS) and the Three Degassing Stations (3DS). However, factors like the social norm take a while to propagate through the population. Hence, long-term experiments were performed to account for that. The most noticeable result was that for both the short-term and the long-term experiments, the 1DS scenario showed a limit value, after which the non-compliance rate would not descend any further. This value appeared at around $IDC/TDC = 0.73$. The reason for this limit value is argued to be the result of waiting times that develop at a certain number of legally degassing ships, making further legal degassing unfavorable. Furthermore, the results showed that deterrence strategies like increasing the severity and certainty of punishment were more effective for the 3DS case over the 1DS case. Finally, little evidence came from the results that the social norm greatly contributed to the compliance rates. Only for a very high certainty of punishment, the population with a larger fraction of agents that were highly influenced by deterrence also affected the agents less sensitive to deterrence through the social norm. This is discussed to be the result of the personal norm. As the calibrated scenario shows a large non-compliance rate, the personal norm quickly shifts to prefer non-compliance. For agents that value the personal norm highly, this will cause them to maintain this non-compliance.

For the ILT, these results imply that the ability to comply is an important factor when discussing regulation. So, the discussion has to include both deterrence, in the form of certainty and severity of punishment, and enabling compliance. The combined framework showed some promising performance. However, also certain limitations were found. The social and personal lacked robustness, resulting in a major importance of the first decision, as it could define the behavior for the rest of the run. Also, the psychological effect of inspections was not taken into account. For future research, considering these factors can improve the TPB-RCT framework. Furthermore, an interesting angle of future exploration for the ILT is described.

10.1. Answers to the Sub-questions

Thus, that leaves only the sub-questions and the research question to be answered. First, the sub-questions are discussed.

> ***Sub-question 1:*** *How can decision-making regarding compliance behavior be described, considering personal and social factors?*

For the decision-making mechanism, the Theory of Planned Behavior (TPB) was enhanced with the Rational Choice Theory (RCT). This was done in a similar fashion to Wu et al. (2021), who used it to study compliance with medical recommendations. However, Wu et al. (2021) replaced the personal norm with a cost-benefit analysis, while the literature mentioned that as an important factor when considering compliance and deterrence (Grasmick & Bursik, 1990; Bachman et al., 1992; Wenzel, 2004). So, instead of omitting the personal norm, a cost-benefit analysis was combined with the TPB as an additional factor. Thus, a combination of a psychological framework with an economic framework to capture the influence of deterrence on both aspects. The combined framework was then conceptualized as suitable for an Agent-Based Model (ABM). Promising results came forth from this combined framework regarding the different cases for which the influence of deterrence was tested. However, some limitations are also acknowledged. Some are related to conceptualizing the framework, like which factors are included. Considerable flexibility is given by using this framework. However, not the full potential of the flexibility was utilized. Factors like the normative norm, what others want an individual to do, and autonomy, what influence others have on the decision, were missing. Also, a more robust implementation of the personal norm might have produced better results. However, even without these improvements, the combined framework showed some promise. Hence, the TPB-RCT framework can be used as a decision-making framework for exploring compliance behavior that considers personal and social factors and economic factors.

> ***Sub-question 2:*** *Assuming the images of Kagan and Scholz (1980), what is the influence of different population compositions, with different fractions of actors following a certain image, on the effect of deterrence?*

Kagan and Scholz (1980) mention three different images which consider compliance differently and will also react differently to deterrence. Out of these three images, two were chosen, the Amoral Calculator (AC) and the Political Citizen (PC), as these images were assumed to be reactive to deterrence in some way, directly or indirectly. In the short term, little influence on the non-compliance rate is found from different compositions of the population. The only difference that is present is in the pattern of the curves. Populations with higher ACs contributions show a delayed reaction to increasing the certainty and severity of punishment. However, the same compositions show a stronger reaction when these policies gain traction within the population. Long-term, the populations with more ACs display to be more reactive towards increasing deterrence. This means that the more Amoral Calculators there are in a population, the lower the non-compliance rate will be when increasing the certainty or severity of punishment. However, interestingly, as the AC values the economic factors that highly, the image is also more recipient to the waiting times that will increase when more ships are degassing legally.

So, different population compositions do matter when considering the effectiveness of deterrence. Deterrence shows its biggest effect the larger the group of Amoral Calculators represented in the population, partially due to the lack of indirect effects that are observed. Hence, to decide the most effective policy, the drivers behind the decision-making of a population have to be considered, as well as how these drivers define the population. If most of a population is not motivated by economic factors, deterrence will not have the intended effect and might even be counterproductive.

> ***Sub-question 3:*** *What influence does an environment that enables or impedes compliance have on the effect of deterrence?*

The environment was one of the most prominent factors determining the non-compliance rates. The One Degassing Station (1DS) case represented a situation where it is hard to degas legally without wasting an unreasonable amount of time. Hence, an environment impeding compliance. On the other hand, the Three Degassing Stations (3DS) case represented a situation that enables compliance, as travel times are significantly shorter than for the 1DS scenario. This resulted in a limited achievable minimal non-compliance rate for the 1DS scenario. The observed limit did not depend on the certainty or severity of punishment. However, it might have depended on the capacity of degassing stations or the amount of (legal) degassing done. For the 3DS scenario, the same limit was easily passed with increasing deterrence, already showing the influence of the environment on the effects of deterrence. Still, for low deterrent regulations, the 3DS environment did not perform better than the 1DS scenario. However, at some point of severity and certainty of punishment, the 3DS scenario appeared to improve the effects of deterrence. So, an environment can have a significant impact on the effect of deterrence, resulting in stronger reactions to deterrence the moment the environment enables compliance.

The environment during this research represented the ability to comply, which fit the case study. However, in different cases, the ability to comply might be subject to other factors and not necessarily the environment. So, the ability to comply might need a different approach for a different case, which can lead to a distinct conclusion.

10.2. Answer to the Research Questions

The final question that has to be answered is the main research question:

> ***Research Question:*** *What is the effect of deterrence on compliance rates when a population's decision-making can be influenced by social and personal factors?*

The simulated population consisted of two of the three different images of compliance behavior, following the study of Kagan and Scholz (1980). One of the images was the Amoral Calculator (AC), an economically rational individual who is mainly profit-driven. The other was the Political Citizen (PC), which values the personal norm it acquired more than profits but might also be influenced by what others think. Theoretically, the AC is easily swayed into compliance by following deterrent regulation strategies. However, it is more difficult to persuade the PC with an economic approach that is deterrence. Still, the PC might be influenced by its social relation to ACs. This could result in the Political Citizen being indirectly influenced by deterrence strategies.

To research exactly that theoretical influence, an attempt is made to isolate that concept in deterrence research. Different scenarios were tested with different environments and different population compositions. The images were distinguished by strongly contrasting weights related to their preferences. So, ACs were heavily skewed towards economic values and PCs strongly toward personal and social factors. However, the results did not provide strong evidence to argue for a large effect of indirect influence of deterrence. It did show for an extreme case of punishment probability that populations with more Amoral Calculators, who were affected by deterrence, had a steeper decline in non-compliance rates for Political Citizens. This could arguably be the effect of the social norm shifting in favor of compliance and, therefore, indirectly shifting PCs to be more compliant. However, this pattern only presented itself in extreme cases. In different, less extreme scenarios, the conclusion can be drawn that a strong personal norm will cause deterrence to have little effect, both directly and indirectly.

To isolate the pattern of the indirect effect of deterrence, extreme measures were taken, like large preference differences between ACs and PCs, various scenarios, and strong increases in deterrence measures. Since, even under these extreme circumstances, a marginal indirect impact of increasing certainty and severity of punishment is found, it is highly doubtful it will present itself under less extreme circumstances, for example, a less polarized population or smaller increases in deterrence measures.

Hence, deterrence has a smaller effect when a population values the personal and social factors more than the economic aspects of compliance. Additionally, no indirect effects that will enhance the effects of deterrence have been found through psychological factors.

10.3. Scientific contribution

The scientific contribution of this research is the exploration of compliance theories with the help of a combination of two different frameworks. One of the frameworks is and has often been used for compliance research, the Rational Choice Theory (RCT). The Theory of Planned Behavior (TPB), on the other hand, is a prominent framework in behavioral sciences and can be used to incorporate concepts such as personal and social norms and a control factor. Such factors appear to have a significant effect when discussing compliance behavior. Hence, combining the two frameworks can enhance the research on compliance behavior.

By using Agent-Based Modeling (ABM) and with a case study, the possibilities of the TPB-RCT framework are explored. The results show some positive performance. However, these results are case-specific. Thus, little generalizability can be expected. So, the combined framework might need to be implemented for different cases. Different cases require different implementations of the framework. However, the TPB-RCT framework displays a flexibility that makes it adaptable to many different situations. To accomplish that, new components can be added, or current components could be converted to fit the case. An example of flexibility and adaptability is shown in the recommendations for future research (Section 9.4).

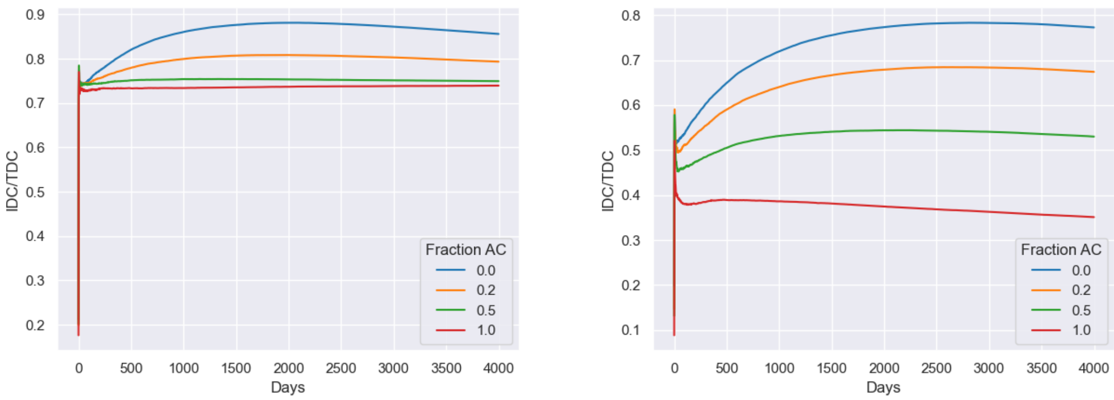
10.4. Societal contribution

An underestimated perspective is emphasized by exploring different aspects of deterrence and regulation. Deterrence is often considered a means of regulation. However, this research shows that in some cases, it is better to ask what the logic behind non-compliant behavior is and how compliant behavior can be made more interesting. In this case, for instance, the effectiveness of deterrence is correlated to the perceived ability to comply with regulations. When it gets harder to comply, people will be less inclined to and, therefore, be less sensitive to deterrence. On the other hand, this research also showed that solely focusing on improving the ability to comply does not automatically improve compliance rates. Hence, both improving the ability to comply and deterring non-compliance should be considered when discussing regulation. Hence, this research's societal contribution is that it emphasizes the importance of both sides of the same coin, that is, regulation.

A
Additional Results

A.1. Fine Cost Analysis for Long-term Runs

In Figure A.1b, the fraction of illegal degassing is shown over the number of days for the scenario with One Degassing Station (1DS) and Three Degassing Stations (3DS), and $C_F = 120$.

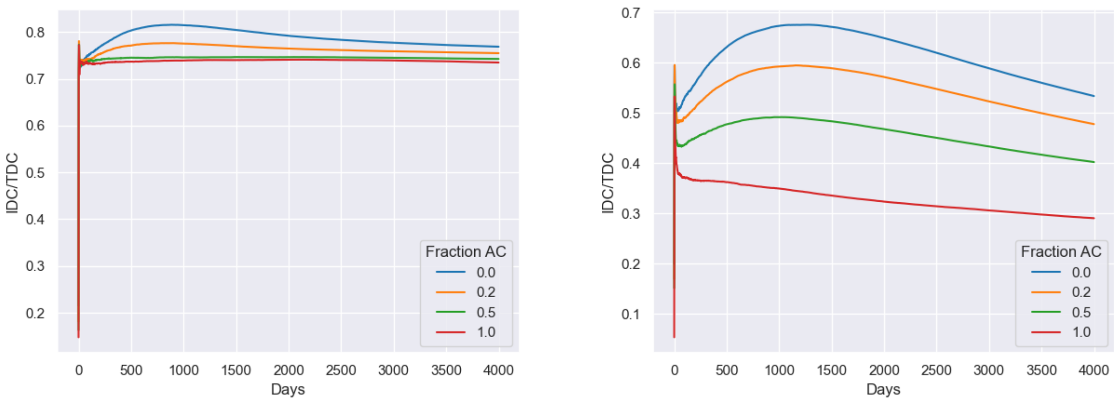


(a) 1DS: $C_F = 120$

(b) 3DS: $C_F = 120$

Figure A.1: Fraction of illegal degassing in time for two degassing station scenarios at $C_F = 120$.

A.2. Probability of Punishment Analysis for Long-term Runs



(a) One Degassing Station (1DS): $P_{punish} = 0.75$

(b) Three Degassing Stations (3DS): $P_{punish} = 0.75$

Figure A.2: Fraction of illegal degassing in time for two degassing station scenarios at $P_{punish} = 0.75$.

A.3. Indirect Effect of Increasing the Cost of the Fine

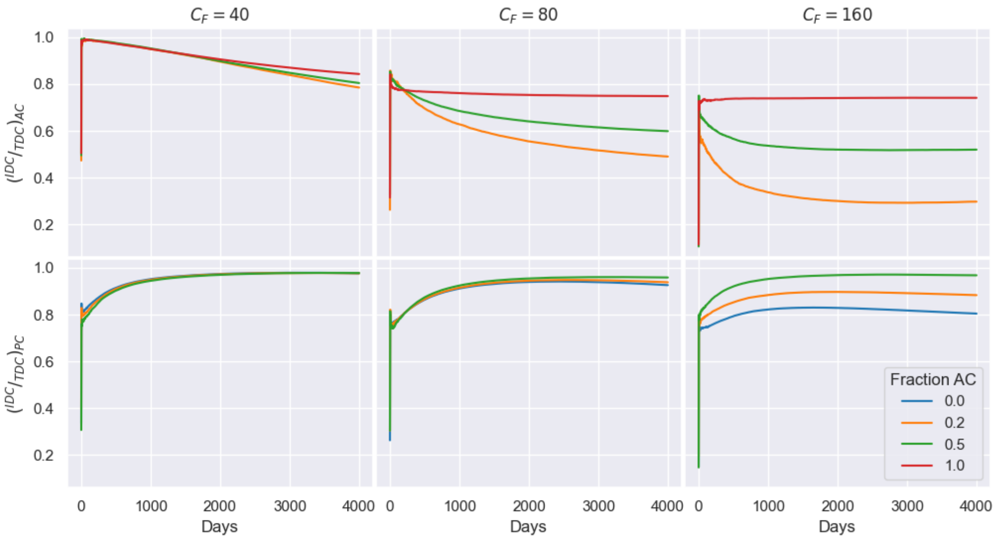


Figure A.3: Fraction of illegal degassing over total degassing for the Amoral Calculators (AC), shown in the upper figures, and the Political Citizens (PC), shown in the lower figures. Shown for 3 different fine costs. One Degassing Station (1DS)

B
Data Used for Assumptions and Calibration

Figure B.1 shows the location of the E-noses. The different colors represent different environmental agencies. A high density of e-noses can be observed in the proximity of Amsterdam and Rotterdam, and also around Moerdijk, where the degassing station is, there are quite a few e-noses. However, other waterways lack e-noses, so little information about illegal degassing can be obtained from those locations.//

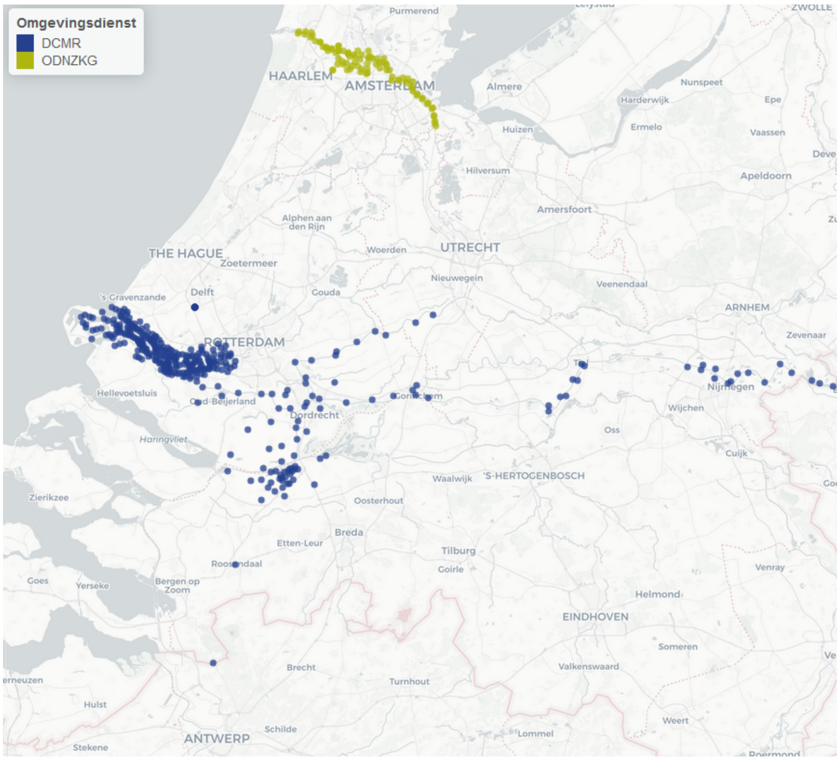


Figure B.1: E-nose locations

In Figure B.2 the number of trips done by every ship over a period of 100 days is shown. Then a normal distribution is fitted over the data, so an estimate can be given to the number of trips agents in the model should perform in 100 days. The fitted normal distribution has a $\mu = 29$ and $\sigma = 14.14$.

As can be seen in Figure B.3, 164 ships have been identified by the pattern in six weeks. This means that roughly 28, rounded up, ships are identified weekly. However, experts mention that around 50% are false positives, which means an estimated number of illegally degassing ships equal to 14 per week. This is from data gathered from six regions in the Netherlands in proximity to Rotterdam and Amsterdam.

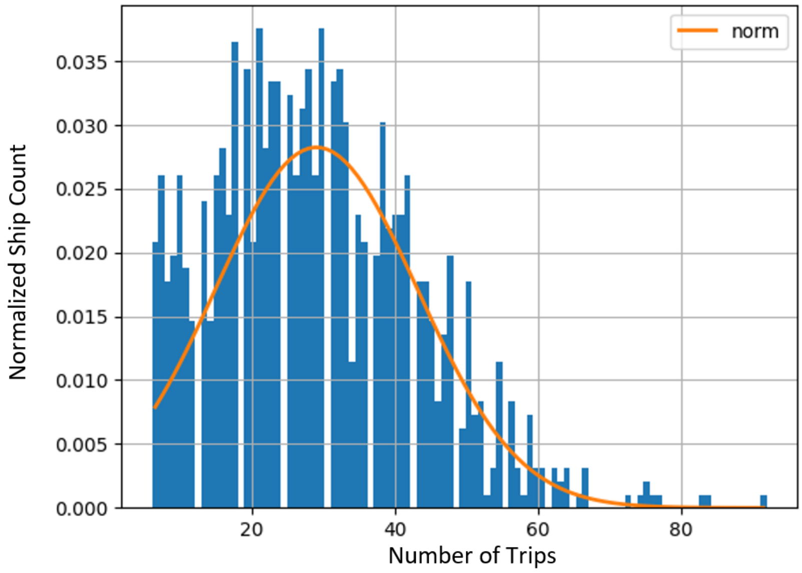


Figure B.2: Number of trips done by the ships in the Netherlands over a period of 100 days

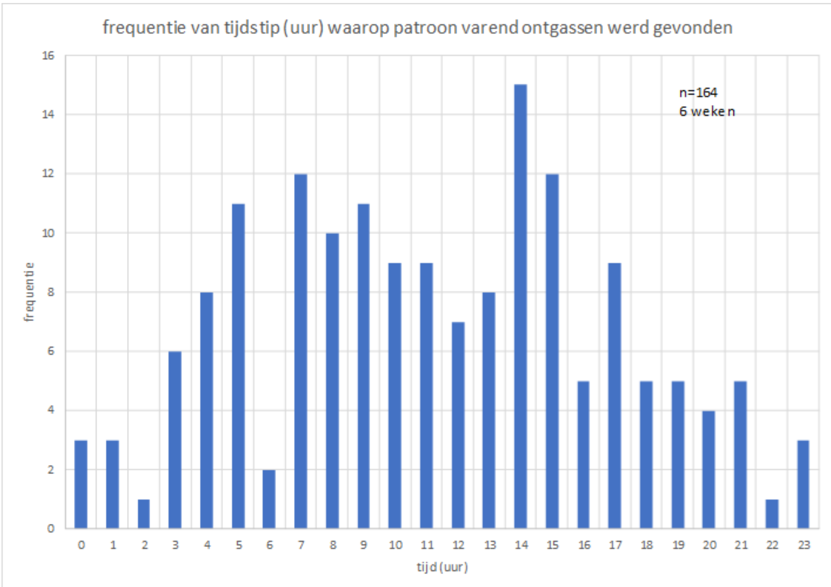


Figure B.3: Number of potential illegally degassing ships based on pattern recognition

Some other estimates were given by inspectors to add to the picture of the amount of illegal degassing in the Netherlands. These are shown in Table B.1. There are many different estimations for the illegal degassing that is happening currently in the Netherlands. Hence, a range of illegal degassing counts between around $70 - 250$ could be viable.

In Table B.2, degassing estimates are given for the substances that are considered for the upcoming ban. These are retrieved from the report by Koop (2016). The estimates are based on Informatie- en Volgsysteem (IVS) data to observe subsequent loads and the compatibility of the loads. What is not taken into account in these estimates is the degassing between loading the same cargo but from different clients and preemptive degassing so a ship is more flexible when deciding on the next cargo, which happens according to the inspectors. So, the estimates might be on the low side.

[1] https://www.nt.nl/binnenvaart/2023/01/24/tankvaart-in-de-knel-bij-ontgassingsverbod/?gdpr=accept

Table B.1: Estimates of inspectors about legal and illegal degassing and punishment frequency

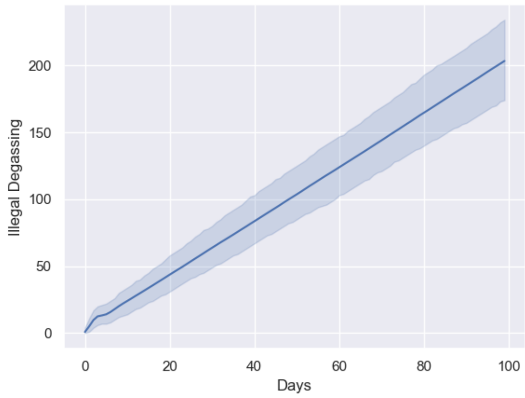
Description	**Estimate**	**Estimate for 100 days**	**Source**
Amount of legal degassing at a degassing station	Average of 15 per month	50	News article mentioned by inspectors [1]
E-nose signals received by the inspectors of ships identified to be degassing illegally	$20-40$ per month	$67-133$	Inspectors
Inspectors boarding a ship to complete a report on potential illegal degassing	At most twice a week	$0-29$	Inspectors
Total E-nose signals	3692 over 1.5 years	613	Heuff (2021)
Potential offenders from the E-nose signals	1404 over 1.5 years	233	Heuff (2021)
Potential offenders from pattern recognition	14 per week	200	Figure B.3

Table B.2: Estimates of the yearly degassing needs of the substances mentioned in the upcoming ban (Retrieved from Koop, 2016)

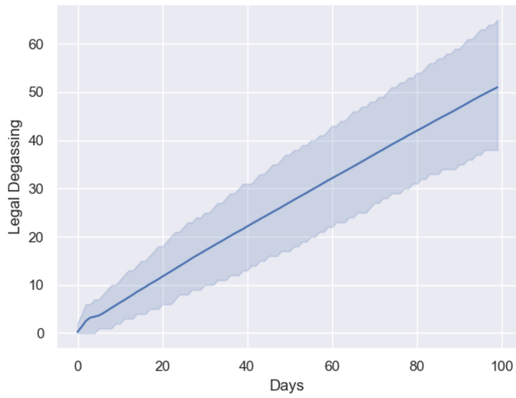
UN-number	**Description**	**Estimated degassing volume**
UN1114	Benzene	241
UN1267	Petroleum crude oil (>10% Benzene)	32
UN1268	Petroleum distillates (>10% Benzene)	2105
UN1993	Flammable liquid (>10% Benzene)	126
UN3295	Hydrocarbons (>10% Benzene)	670
UN3475	Ethol and Pertol mixtures (>10% Benzene)	24
Total		**3197**

B.1. Results from the Calibration

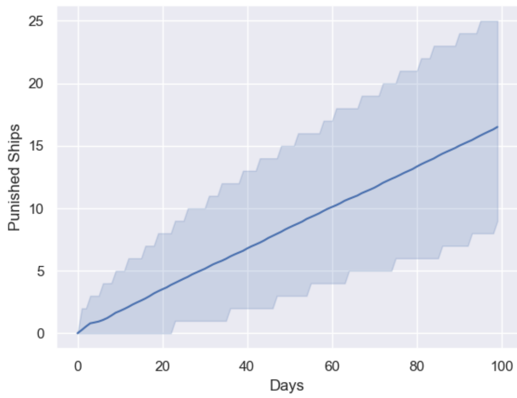
Figure B.4 shows the final outcomes of the calibrated model. The number of illegally degassed ships is on average 210, legally degassed ships on average 52, and punished ships on average 16, which is all close to the estimates given. These counts are achieved with the model values as mentioned in Section 6.5.



(a) Illegal degassing



(b) Legal degassing



(c) Punished ships

Figure B.4: Counts for the different calibrated outcomes

C
BPMN Model

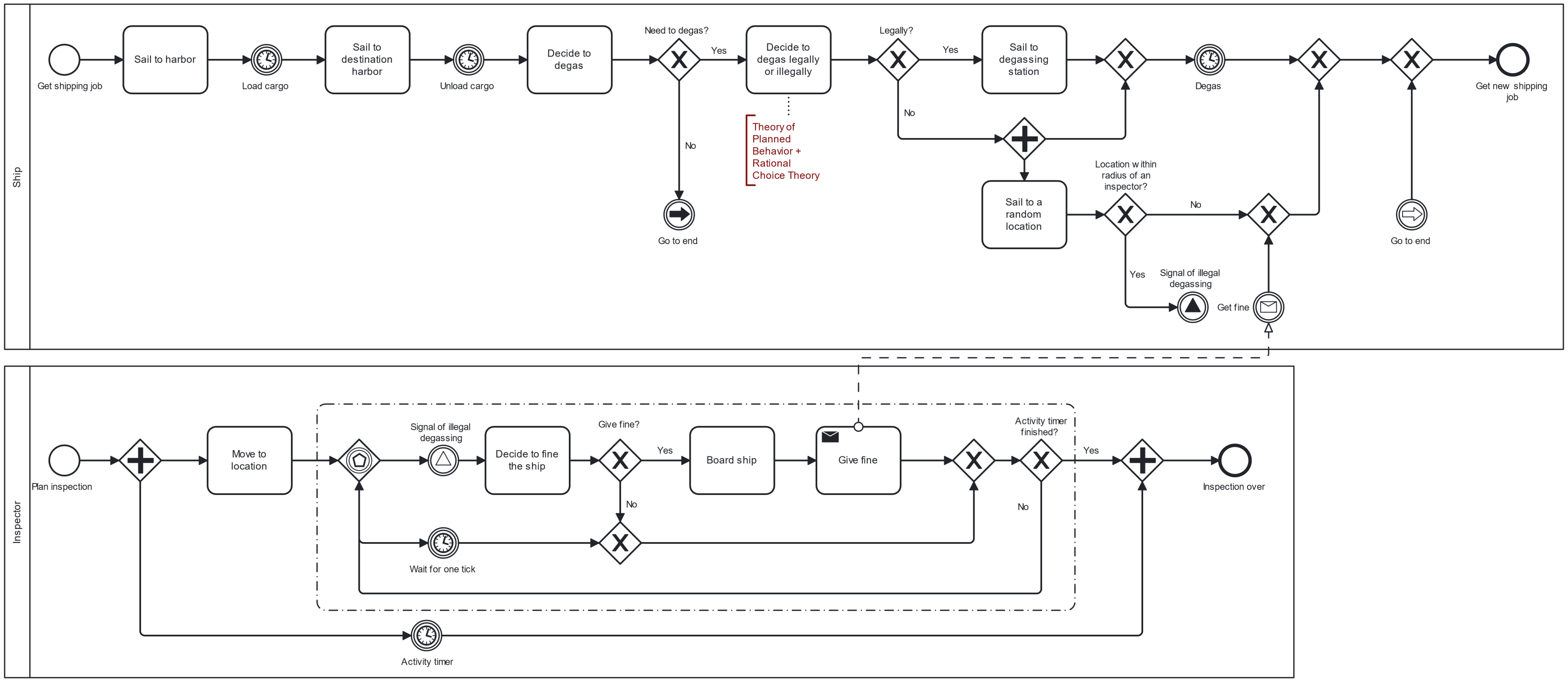


Figure C.1: BPMN model of the behavior of the agents in the Agent-Based Model

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