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# What drives the Rebound Effect in transportation? An evaluation based on a Traveling Purchaser Problem

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*Nam Causa*

# Abstract

Limiting climate change is one of the most important challenges of the 21st century. Focusing on the transport sector, encouraging the use of more energy-efficient transport modes, and improving the performance of vehicles are the main targets in the fight for GHG reductions. However, due to Rebound Effect (RE), it is proven that improvements in engine fuel efficiency result in lower cost per kilometer driven and can induce individuals to use vehicles more often or to drive longer distances. As a result, the potential energy savings from improved energy efficiency could be partially or totally offset. Therefore, we decided to examine "What drives the Rebound Effect in transportation".

To answer this research question, a Traveling Purchaser Problem was evaluated. This simple real-life business application models a situation in which a company owns one or several vehicles and has to buy specific products. The goal is to select and visit a subset of suppliers to satisfy a given demand for each product while minimizing both purchasing and travel costs. In total, 510 instances of this problem with various characteristics and parameters were generated and solved using the optimization software AIMMS. The impact of five main experimentations was deeply investigated. In addition, the trends obtained from these experiments were confirmed by fitting a logistic regression and a decision tree.

The results of the various experiments showed that four variables can influence the occurrence of RE in a transportation network. On the one hand, RE tended to increase with the number of potential suppliers from which the firm can choose and the number of vehicles that the company owns to procure the products. On the other hand, the exclusivity of the products to source, as well as the introduction of a distance-traveled tax, reduced the occurrence of RE. To sum up, significant conclusions could be drawn from the experiments and the results can be easily transferred to real-life business applications. Recommendations for possible future studies were also discussed.

**Keywords** - Rebound Effect, Transportation, Traveling Purchaser Problem, Modeling

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# Acronyms

***f*** Fuel Efficiency

**ATPP** Asymmetric Traveling Purchaser Problem

**B&B** Branch-and-bound

**B&C** Branch-and-cut

**BF** Backfire

**DT** Decision Tree

**GHG** Greenhouse gases

**LP** Linear Program

**MILP** Mixed Integer Linear Program

**RE** Rebound Effect

**STPP** Symmetric Traveling Purchaser Problem

**TPP** Traveling Purchaser Problem

**TSP** Traveling Salesman Problem

# Chapter 1

# Introduction

Limiting climate change is one of the most important challenges of the 21st century. In 2015, during COP21, 196 Parties agreed on the Paris Climate Agreement which set the main goal of limiting global warming to 1,5 degrees Celcius. To do so, net $CO_2$ emissions must be reduced to zero by 2050 at the latest. Nevertheless, according to the IPCC report (2022b), this scenario is very optimistic given the current GHG emissions level and rapid major transitions that need to be taken to mitigate climate change and avoid some disasters.

Among those transitions, we find the deployment of low-emission energy sources, the decrease in fossil fuel consumption, and energy efficiency and conservation. That is why over the past few years, we have seen a tremendous amount of new laws and policies aiming at reducing GHG emissions in sectors such as energy or transportation. However, improvements in energy efficiency usually make energy services less expensive and thus, encourage increased consumption of those services. The expected savings from the efficiency improvement could be therefore partially or totally offset. This phenomenon is called the Rebound Effect and its relevance in the policy domain is blowing up.

In addition to being particularly subject to Rebound Effects, transportation is among the most $CO_2$ emitting sectors. That is why we decided to study the occurrence of this phenomenon in this specific sector.
Besides, we will study applications that could be compared to simple real-life cases. Thus, we based our approach on a Traveling Purchaser Problem in order to model various applications similar to simple business problems. As a matter of fact, the thesis aims

to answer the question *"What drives the RE in transportation?"* through a Traveling Purchaser Problem.

Concerning the structure of the thesis, it is arranged as follows. Chapter 2 presents the general context of our thesis. It examines the impact and cause of climate change as well as the mitigation strategies used to tackle it. The importance of taking into account the rebound effect for climate policy development is also pointed out. In addition, the research question of our thesis will be specified. Chapter 3 provides a literature review about the concept of Rebound Effect. The Traveling Purchaser Problem and its different variants are also presented. Chapter 4 shows the model we built as well as the method we use to solve it. Chapter 5 explains how we generated the data. Chapter 6 contains a numerical application of our model and details the methodology that we used for the experiments. Chapter 8 offers a discussion about the results and how we can interpret them. Chapter 9 draws conclusions, and explores the limits and potential future research.

# Chapter 2

# Context

## 2.1 Impact of Climate Change

Since the IPCC Fifth Assessment Report was released in 2014, disruptions caused by climate change have become even more dramatic. In reality, the magnitude and extent of the damages are worse than what was predicted (IPCC, 2022a).

First, significant and increasingly irreversible damages have been done to the marine and terrestrial ecosystems all over the world. The increase in global temperature, melting of glaciers, rising sea levels, and changes in global precipitation patterns are all consequences of climate change. These phenomena impact the various species living in the ecosystems. One of the most striking examples is undoubtedly the disappearance of local animal species due to rising temperatures. In addition, the IPCC report's predictions concerning the survival of animal species are much more alarming. With an increase of 1,5 degrees, 3 to 14% of terrestrial species could disappear. In the worst-case scenario, we could reach 48% extinction by the end of the century, if the warming level reaches 5°C (IPCC, 2022a).

Secondly, climate change also impacts human health. On the one hand, diseases related to food and water access are increasing. Indeed, around 50% of the world's population faces severe water shortages once a year for at least one month. It has the effect of increasing health risks in those regions. On the other hand, extreme heatwaves become more common in cities, causing heat-related cardiovascular diseases (IPCC, 2022a).

Then, it is undeniable that economic damages have also been caused by climate change in climate-exposed sectors like fishery, tourism, agriculture, and forestry. For instance, tropical cyclones or the loss of crops due to droughts reduced the economic growth of the regions affected by these disasters (IPCC, 2022a).

In conclusion, the current and future influence of climate change on both natural and human systems is undeniable.

## 2.2 Cause of Climate Change

Although other Greenhouse gases (GHG) and pollutants influence the climate, it is clear that carbon dioxide ($CO_2$) is the main driver of climate change. According to IPCC reports, 59 gigatons of $CO_2$ emissions were emitted in 2019 versus 49 gigatons in 2010 (2014; 2022a; 2022b). We can argue that the evidence for human influence on global warming continues to grow.

We usually attribute the GHG emissions to five broad categories: energy supply (34%), transport (15%), industrials (24%), buildings (5%), and finally AFOLU[1] (22%). Of course, each category is defined by its own challenges in terms of climate change mitigation and numerous policies have been introduced over the last decade to face them (Lamb et al., 2021; IPCC, 2022a,b).

## 2.3 Mitigation Strategies

The policies promoted by the international community often fall into one of two categories: adaptation or mitigation policies. On the one hand, mitigation strategies aim at tackling the cause which means lowering or removing GHG from the atmosphere. On the other hand, the purpose of adaptation strategies is to adjust systems and societies to face the impact of climate change. The two types of strategies complement each other and are necessary to reduce and manage the risks of climate change (IPCC, 2014).

Among the most requested mitigation actions, one can mention the improvement of energy efficiency. As a matter of fact, resource conservation through energy efficiency seems to be the easiest and most impactful solution (Herring and Sorrell, 2009; Zhang and Da, 2015; IPCC, 2014, 2022a). In addition, this strategy can be applied to each of the five categories

[1] Agriculture, forestry, and other land use

mentioned before. Energy conservation and efficiency improvement are crucial in the fight against global warming since they would lead to less energy use and therefore fewer emissions emitted into the atmosphere. However, energy savings induced by efficiency improvement are not always fully realized in practice (IPCC, 2014). In some sectors such as transport or electricity, an energy efficiency improvement could lower the unit cost of the service and therefore stimulate the demand (Greening et al., 2000).

If we focus on the transport sector specifically, avoiding or reducing trips, encouraging the use of more energy-efficient transport modes, and improving the performance of vehicles and fuels are the main targets in the fight against global warming (Mundaca et al., 2019). Between 2010 and 2019, modest improvements in the energy efficiency of around 1,5% per year were achieved in this sector (IPCC, 2022a,b). Therefore, a decrease in $CO_2$ emissions was expected. However, the average annual growth of GHG emissions from transport is around 1,8% per year over the same period. It means that potential energy savings were offset by the global increase in passenger and freight travel activity levels (IPCC, 2022a,b). The concept behind this paradox is called the Rebound Effect (RE). Improvements in engine fuel efficiency result in lower cost per kilometer driven and can encourage individuals to use their vehicles more often or to drive longer distances (Steren et al., 2022). Nevertheless, it is not only present on the consumer side. Instead of reducing emissions, car manufacturers used the improved technology to build larger, heavier, or faster vehicles (Pirani, 2018).

As we said earlier, this RE phenomenon is not only limited to the transport sector. For example, between 1972 and 1996, the energy efficiency of new refrigerators has more than tripled. Nevertheless, the expected savings were partially offset because manufacturers increased refrigerators' sizes (Pirani, 2018). The utilization of LED light bulbs is another example of how RE can occur. We can argue that, in principle, switching to a LED light bulb can save both energy and money. However, this is not so evident in practice. Studies have shown that individuals tend to increase their demand for lighting when shifting to more efficient lighting systems, partially offsetting the predicted energy-efficiency gains (Herring and Sorrell, 2009). These two examples are other simple illustrations of the RE.

## 2.4 Relevance of Rebound Effect

As mentioned, the implementation of energy efficiency policies has been one of the main objectives of governments since it has become crucial to reduce energy consumption and GHG emissions. However, it is critical to properly evaluate the actual effectiveness of any energy policy that aims to promote energy efficiency improvements because it has been proven that RE can occur (Llorca and Jamasb, 2017; Steren et al., 2022). The expected energy savings induced by the improvement in energy efficiency could be only partially realized or even completely offset (Greening et al., 2000; Jevons, 1865; Orea et al., 2015). Therefore, taking into consideration the potential RE when evaluating these mitigation policies is now essential (Orea et al., 2015; IPCC, 2014, 2022a).

This concept may not be so popular, but it was first mentioned in 1865 by William Stanley Jevons. Since then, many studies and research have been conducted, leading to the recognition of the existence and relevance of RE, not only by authors from the academic field but also in the public policy domain (Vivanco et al., 2016; IPCC, 2014, 2022a).

An illustration of the relevance of this concept in policy-making is the energy conservation in developing countries (Sorrell, 2007; IPCC, 2014, 2022a). In fact, the efficiency improvement may cause a financial gain creating a re-spending effect for both firms and consumers. In addition, people sometimes do not have access to energy services such as household heating. A lower energy price after an efficiency improvement could therefore allow them to start using heating systems. Thus, the overall energy consumption could increase and lead to an important RE (Van den Bergh, 2011).

In conclusion, even if RE was not taken into account by policymakers in the past, it has now started to be considered crucial. Given the increasingly dramatic situation regarding global warming, the number of studies regarding this concept is constantly increasing. These researches proved its relevance as well as the importance of analyzing its potential occurrence when evaluating the actual effectiveness of technological improvements and new policies.

## 2.5 Research Question

As mentioned in the previous sections, the interest in the RE concept has been growing over the last decade. This can be explained by the increasing need to fight against climate change, which concerns the entire world population. Mitigation and adaptation policies are multiplying all over the world to limit global warming and its effects. Besides, a large part of those policies highlights the improvement of energy efficiency as an effective way to mitigate GHG emissions. However, it is argued that energy efficiency improvements, especially in the transport sector, can cause RE. The expected reduction in GHG emissions would therefore be partially or sometimes totally offset due to this phenomenon. Furthermore, the transportation sector represents 15% of the total GHG emitted in 2019, which is not negligible. As a result, evaluating what can lead to the occurrence of RE in this $CO_2$-emitting sector seems crucial.

That is why we decided to focus on RE that could appear in transport and investigate what drives its occurrence. We decided to base our analysis on applications that could be compared to simple real-life cases. Modeling a firm minimizing its procurement and transport cost while meeting demand is one of the most common problems in everyday business life. That is one of the reasons why we will analyze what drives the RE in such an application through a Traveling Purchaser Problem (TPP). Indeed, the latter allows to model and analyze a real-life business problem of reasonable size and solve it. Of course, this TPP will be described in detail in the next chapters.

To conclude, this thesis aims to answer the question *"What drives the RE in transportation?"* and will use a TPP as a tool to analyze the occurrence of RE in a simple real-life business application.

# Chapter 3

# Literature Review

In this chapter, the theoretical framework of the thesis will be set by summarizing the findings of scientific articles, books, peer-reviewed papers, and research center studies.

First, the concept of Rebound Effect will be reviewed by providing historical context, general definitions, and a typology of rebound. The methods and issues encountered to estimate the RE will also be presented.
Then, the Traveling Purchaser Problem will be theoretically introduced, and the classification of the different variants of the problem will be explained.
The last part of this chapter will focus on the relevance of TPP in the RE analysis and a study linking those two topics will be discussed.

## 3.1 The Rebound Effect

### 3.1.1 Historical Context

Energy issues, especially natural resource depletion problems, have been addressed at different stages of economic history. In the middle of the 19th century, coal depletion was a worrying subject. At that time, Britain possessed the highest quality of coal available on the international markets. In combination with leading machinery and commercial strength, Britain was considered the industrial super-power. Therefore, economists tried to make political decision-makers realize what could be the consequences of coal depletion on British industry and the development of their economy. (Missemer, 2012)

William Stanley Jevons focused his attention on that concern in his book "The Coal Question" (1865), retrospectively known for having pointed out the first basis of what we call today the RE (Alcott, 2012). According to him, in addition to the limited supply of coal, the real issue was the rate of consumption of natural resources. Indeed, assuming that this rate was exponential, resource depletion became a significant concern (Missemer, 2012). While tackling this problem, Jevons presaged some of today's biggest topics such as limits to growth, renewable and non-renewable resources, and sustainability (Alcott, 2005).
Based on a study about the impact of steam engine efficiency on the demand for coal, he stated that economically justified energy efficiency improvements would increase rather than reduce energy consumption (Jevons, 1865). This is referred to as the "Jevon's Paradox" in the literature.

Later on, modern economist Saunders (1992, p.131) reformulated Jevon's intuition based on modeling: "*with fixed real energy prices, energy-efficiency gains will increase energy consumption above what it would be without these gains*". This was named the "Khazzoom-Brookes postulate", in reference to Len Brookes and Daniel Khazzoom, two economists that had closely investigated this idea (Sorrell, 2009).

Berkhout et al. (2000) were also interested in the idea behind Jevon's paradox. Indeed, on the producer side, energy is a substantial input to the production function, as well as other factors such as labor and capital. Therefore, an improvement of energy efficiency in the industrial process can result in decreasing the unit production cost and, in the long run, shifting the factors of production. Depending on his market power, the producer can thus set a lower selling price which can stimulate additional demand.

Over the years, more and more researchers have begun to analyze this phenomenon. Indeed, if this paradox turns out to be real, it would have great consequences for policy-makers that aim to limit the consumption of resources and the emissions of GHG.
Different authors have therefore tried to define this phenomenon more precisely, as well as its surroundings concepts such as energy efficiency, energy service, or energy savings.

Moreover, a specific typology has been established in order to classify the different types of RE. Finally, many economists and econometricians have tried to quantify the RE and understand the factors that influence it. Those findings will be summarised in the next sections of this chapter.

### 3.1.2 General Definitions

#### Rebound Effect

The Rebound Effect is a large concept that encompasses a variety of mechanisms reducing or offsetting potential energy savings from improved energy efficiency (Sorrell, 2009). It is usually expressed as a percentage of the expected energy savings. The nature and importance of this phenomenon have been significant topics of the energy economics literature for decades now.

#### Energy Service & Useful Work

In the literature, the RE is usually related to an individual energy service and the energy needed to deliver that service. Indeed, according to Hunt and Ryan (2015) energy is not desired for what it is, but rather for the services that it produces.

Nevertheless, it is quite hard to find a definition on which most practitioners agree. To this extent, based on content analysis, Fell (2017) investigated the concept of energy service and proposed a comprehensive definition. He stated that "*Energy services are those functions performed using energy which are means to obtain or facilitate desired end services or states.*" (Fell, 2017, p.137). Examples of energy services are lighting, heating, refrigeration, and transport (Fouquet, 2008).

Besides, Sorrell (2007) articulated that an essential feature of an energy service is the "useful work" obtained. The idea here is that the energy is being put to work in a way to obtain something that is distinct from the energy use itself (Hunt and Ryan, 2015). For example, for car users, it can be defined in vehicle kilometers or in passenger kilometers (Sorrell, 2007).

In addition to useful work, energy services can also have broader attributes (Sorrell and Dimitropoulos, 2008). To come back to the car example, even though all vehicle offers the same useful work, they can vary widely in terms of characteristics such as speed, comfort, or prestige.

**Energy Efficiency & Savings**

One can argue that energy efficiency improvement will enable to achieve energy savings. However, estimating these energy savings is not an easy task. One reason concerns the cause-effects chains, which are uncertain and unobservable. Indeed, many factors can play a role in the behavioral response of economic agents following an energy efficiency improvement. In addition, other variables such as government policies or economic growth may also impact energy efficiency. (Van den Bergh, 2011; Sorrell, 2007)

Regarding the definition of this concept, Sorrell (2007, p.11) expressed it this way: *"the ratio of 'useful' outputs to energy inputs for a system"*. This system can be a coffee maker, an industrial sector, or the entire economy of a country.

In practice, when researchers want to measure energy efficiency and energy consumption, they will have to define those concepts of inputs and outputs. Of course, this depends on the type of study carried out. Then, the authors will have to determine the system and the period studied. All these choices will directly or indirectly impact the estimation of the RE (Sorrell, 2007).

### 3.1.3 Typology

A typology of rebound effects has been established by Greening et al. (2000). It divides the RE into direct RE, indirect RE, and economy-wide RE.

**Direct Rebound**

From a micro point of view, the direct RE refers to increasing demand for a product or service because a technological improvement in energy efficiency reduced the price of an energy product or service (Greening et al., 2000; Sorrell and Dimitropoulos, 2008).
Here the focus is on whether or not the technological improvement can result in the

expected decrease in energy consumption predicted by simple engineering computations. The answer from economic theory is negative. (Sorrell, 2009)
First, the improvement in energy efficiency will decrease the amount of energy input needed, and therefore lower the unit cost of energy services (Berkhout et al., 2000). As mentioned before, this price decrease may lead to a lower selling price which can eventually stimulate the demand and the consumption of those services (Greening et al., 2000). Next, this raise in consumption might offset some or all of the predicted reduction in energy consumption.

For consumers, the direct RE can be decomposed into a substitution and an income effect (Greening et al., 2000).

- Substitution effect: "*consumption of the (cheaper) energy service substitutes for the consumption of other goods and services while maintaining a constant level of utility, or consumer satisfaction.*" (Sorrell, 2007, p.4)
- Income effect: "*the increase in real income achieved by the energy efficiency improvement allows a higher level of utility to be achieved by increasing consumption of all goods and services, including the energy service.*" (Sorrell, 2007, p.4)

Furthermore, a similar decomposition can be applied for producers between the substitution and output effect.

- Substitution effect: "*the cheaper energy service substitutes for the use of capital, labor, and materials in producing a constant level of output.*" (Sorrell, 2007, p.4)
- Output effect: "*the cost savings from the energy efficiency improvement allows a higher level of output to be produced - thereby increasing consumption of all inputs, including the energy service.*" (Sorrell, 2007, p.4)

**Indirect Rebound**

The indirect RE refers to the consumer's increase in demand for other energy products or services, given that his income (or time) increases with the price reduction of a given energy product or service (Greening et al., 2000).

Indeed, even if there is no direct RE for an energy product or service, global energy consumption could still be less than what simple engineering calculations suggested (Sorrell, 2009). For example, in a situation where a consumer does not drive more with his fuel-efficient car, he can still spend the saved money on other goods or services that are also energy-intensive.
This effect has to be taken into account by policymakers as it could weaken the interest for products considered as ecologically desirable (Sorrell, 2009).

Similar to the direct RE, it is convenient to decompose the indirect RE in embodied energy and secondary effects (Sorrell, 2007).

- Embodied energy: "*the indirect energy consumption required to achieve the energy efficiency improvement, such as the energy required to produce and install thermal insulation.*" (Sorrell, 2007, p.4)

- The secondary effects: "*the consequence of the energy efficiency improvement*" (Sorrell, 2007, p.4), which includes the mechanisms listed in Figure 3.1.

*Embodied energy effects*: The equipment used to improve energy efficiency (e.g. thermal insulation) will itself require energy to manufacture and install and this 'embodied' energy consumption will offset some of the energy savings achieved.

*Re-spending effects*: Consumers may use the cost savings from energy-efficiency improvements to purchase other goods and services which themselves require energy to provide. As an extreme example, the cost savings from a more energy-efficient central heating system may be put towards an overseas holiday, leading to an increase in kerosene consumption.

*Output effects*: Producers may use the cost savings from energy-efficiency improvements to increase output, thereby increasing consumption of capital, labour and materials which themselves require energy to provide. If the energy-efficiency improvements are sector wide, they may lead to lower product prices, increased consumption of the relevant products and further increases in energy consumption. All such improvements increase the overall productivity of the economy, thereby encouraging economic growth, increased consumption of goods and services and increased energy consumption.

*Energy market effects*: Large-scale reductions in energy demand may translate into lower energy prices which will encourage energy consumption to increase. The reduction in energy prices will also increase real income, thereby encouraging investment and generating an extra stimulus to aggregate output and energy use.

*Composition effects*: Both the energy-efficiency improvements and the associated reductions in energy prices will reduce the cost of energy-intensive goods and services to a greater extent than non-energy-intensive goods and services, thereby encouraging consumer demand to shift towards the former.

Figure 3.1: Indirect RE (Sorrell, 2009, p.1457)

### Economy-Wide Rebound

At the macro-level, the sum of these direct and indirect effects is the overall or economy-wide RE. For example, an economy-wide RE of 100% means that the potential gains from energy efficiency improvement have been completely offset.

It can be explained by the following reasoning. In the production process, the improvement in energy efficiency induces that all energy products consume much less, resulting in a decrease in costs and therefore an increase in profits. Subsequently, all energy product businesses will expand their production scales which will finally increase the energy demand. (Sorrell, 2007)

It is important to note that at the micro-level, the overall RE equation does not stand anymore since the economy-wide rebound effect does not apply (Thomas and Azevedo, 2013).

### Illustration

To conclude this section about the typology of rebound, it is interesting to have a look at Figures 3.2 and 3.3. These summarize the mechanisms of direct and indirect RE for consumers and producers, respectively.

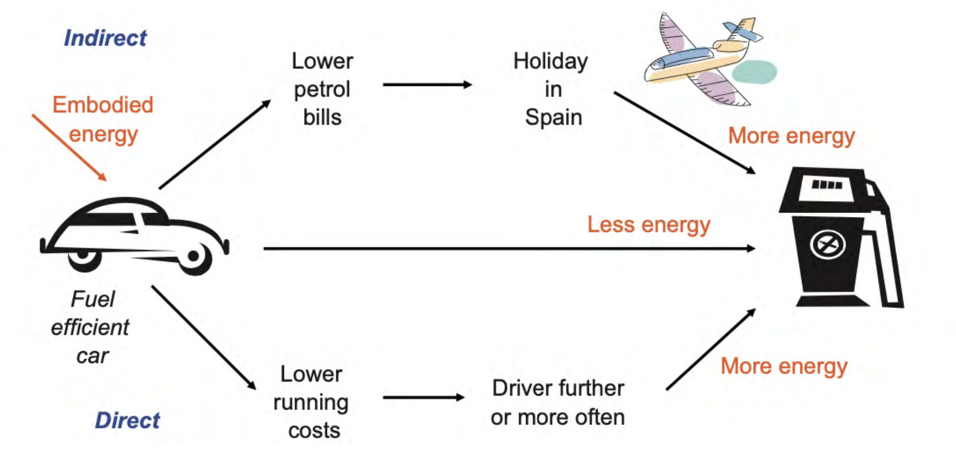



Figure 3.2: Illustration of RE for consumers (Sorrell, 2009, p.1458).

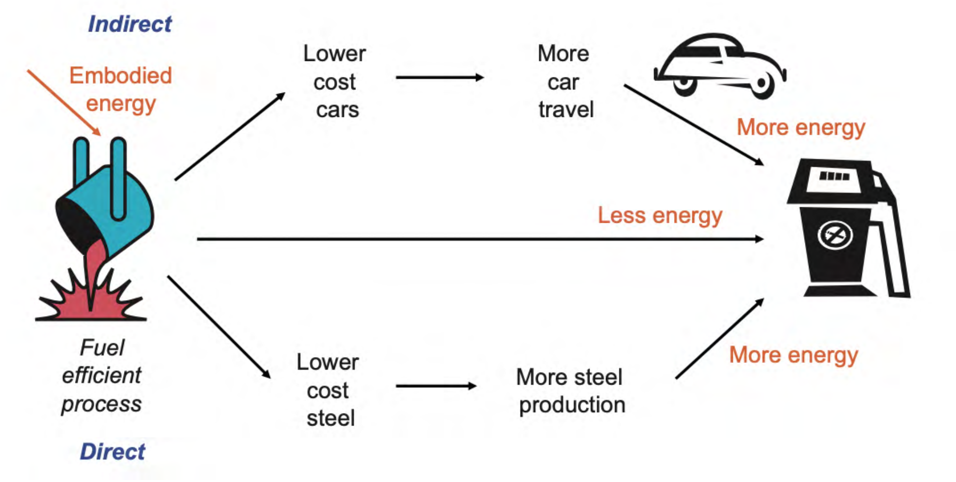



Figure 3.3: Illustration of RE for producers (Sorrell, 2009, p.1458).

### 3.1.4 Estimating the Rebound Effect

As mentioned previously, when an efficiency improvement occurs, we expect energy savings to be realized. Nevertheless, benefits from this improvement are usually partial because of consumer and market response. We can now define the RE in the simplest way possible :

$$RE = 1 - \frac{Actual\ Savings}{Potential\ Savings}$$

On the one hand, "Potential Savings" indicate the expected energy savings. These are computed based on the idea that individuals will maintain their consumption habits. It means that no market or consumer response will happen after the efficiency improvement. On the other hand, the "Actual Savings" define the energy savings that actually happen after the efficiency improvement (Jaehn and Meissner, 2022; Stern, 2020).

We can illustrate this with the example of the purchase of a better energy-efficient car. Potential savings are the gains that would be made if the individual did not change their driving habits. The individual would travel the same distance as before but with a more efficient car. Therefore energy gains would be achieved. However, in reality, after purchasing a more efficient car, consumers may tend to drive further and more often than before. Therefore, the actual savings would be lower than expected. We would face a partial RE. Furthermore, we can also observe a Backfire (BF) when the RE is greater than 100%. This means that after the efficiency improvement, we ended up consuming more energy compared to the initial situation. In fact, no energy savings were actually realized. (Sorrell, 2007; Alcott, 2005; Sorrell, 2009; Small and Van Dender, 2007)

#### Measuring Indicators

The measuring indicators developed by Saunders (1992) are the most widely used and the most representative ones at the macro-economic level (Zhang et al., 2017). It describes energy savings by improving energy efficiency as its elasticity. The following formula can be used to assess the RE:

$$RE = 1 + \epsilon_E$$

where $\epsilon_E$ represents the elasticity of demand for energy with respect to energy efficiency.

However, since measuring $\epsilon_E$ is usually difficult, it can be replaced with one of the following elasticities (Sorrell, 2007) :

– E2 = the elasticity of the demand for useful work with respect to energy efficiency.

– E3 = the elasticity of the demand for useful work with respect to the price of useful work.

– E4 = the elasticity of the demand for useful work with respect to the price of energy.

– E5 = the elasticity of the demand for energy with respect to the price of energy.

(E4) and (E5) are the most used in the literature since they both require data on energy prices, which is easier to collect than data about useful work or energy efficiency (Sorrell, 2007). That is why for sectors such as transport, heating, and lighting, this type of data will be used since it can be easier to obtain (Thomas and Azevedo, 2013). However, using data on energy prices can be valid only if two conditions are met. First, energy efficiency is not affected by variations in energy prices. Second, the behavioral response of consumers to a decrease in energy prices must be the same as an improvement in energy efficiency (and vice versa) (Sorrell, 2007).

The RE estimated from this indicator can be classified into five categories based on its magnitude (Zhang et al., 2017):

| **Size** | **Type of RE** | **Explanation** |
|---|---|---|
| RE<0 | Super Conservation | The real energy savings are more than the expected one due to improving energy efficiency. |
| RE=0 | Zero Rebound | The expected energy savings are fully achieved. |
| 0<RE<1 | Partial Rebound | The energy savings by improving energy efficiency are partially offset. |
| RE=1 | Full Rebound | The expected energy savings are fully offset. |
| RE>1 | Backfire | The improvement of energy efficiency causes an increase in energy consumption. |

Table 3.1: Five categories of RE developed by Saunders (1992).
(Zhang et al., 2017, p.151)

As a side note, one can argue that the super-conservation is highly counter-intuitive. A hypothetical example can be found with solar energy (Wei, 2010). Indeed, because solar energy is produced from labor, capital, and sunlight and the latter is considered clean, we can ignore it from the production system. Therefore, solar energy can be considered as a product of only labor and capital. To a larger extent, if energy input can be replaced with solar energy in most production processes, the demand for energy would tumble and the super-conservation effect can happen.

Nevertheless, this is not likely to happen in the short term because the substitution between energy and other factors is significantly restricted on a global scale (Wei, 2010).

**Estimation Issues**

Plenty of authors argue that accurately estimating the RE is not an easy task. In fact, many empirical studies ended up underestimating the real effect due to very likely upward biases (Sorrell, 2007; Sorrell et al., 2009; Alcott et al., 2012). There are several reasons for those conclusions.

First, according to the energy service studied, the necessary data are sometimes unavailable. Therefore, they must be estimated which makes it subject to errors. (Sorrell, 2007; Sorrell et al., 2009)

Second, RE can be estimated with the Saunders Indicator (1992) in which elasticity involving the useful work is used. Nevertheless, only aggregate measures of useful work for few energy services are easily accessible. That is why many studies in automotive transport literature have been carried out. Of course, it is also possible to collect disaggregated measures but at much higher costs. For instance, studies in the household heating sector have used expensive monitoring to control the thermal temperature accurately (Sorrell, 2007). Monitors had to be set up outside and in all rooms inside to quantify the consequences of an improvement in energy efficiency. In addition, other factors such as air velocity, relative humidity are decisive in thermal comfort and not taking them into account could lead to biased estimates of the direct RE (Sorrell, 2007; Fanger et al., 1970; Frey and Labay, 1988; Friedman, 1987).

Third, estimating indirect effects is a real challenge given the number of confounding variables. For example, from the producers' point of view, changes in raw material prices and in production costs would appear after an energy efficiency improvement (Freire-González, 2011). It is therefore difficult to quantify all indirect use of energy throughout the economy after (Sorrell, 2007; Van den Bergh, 2011). This is the reason why many studies focus on direct rebound estimates. They require fewer assumptions, are less prone to bias errors, and therefore lead to more reliable results.

Fourth, geographic, demographic or other exogenous variables can have a crucial influence on the RE since they can cause changes in energy demand, useful work, or energy efficiency. Once again, difficulties arise when measuring those factors or deciding which should be included in the model or not (Sorrell, 2007; Sorrell et al., 2009; Van den Bergh, 2011).

Finally, the need to include international dimensions (transboundary effects, trade, relocation) and long-term dynamics (technological change, economic growth) is another reason why estimating the rebound effect is hard (Van den Bergh, 2011).

In conclusion, we can easily notice how difficult it is to accurately estimate the RE.

**Estimation Methods**

The direct RE can be estimated with two different approaches. On the one hand, evaluation studies consist of measuring the change in demand for useful work after an energy efficiency improvement (Sorrell, 2007). It is based on the use of primary data obtained from surveys (Freire-González, 2011). However, as mentioned before, measuring the demand for useful work for many energy services is very difficult because it can be influenced by several exogenous other factors. Alternatively, one can argue that we can measure the change in energy consumption after improving energy efficiency, and compare this with one of the following counterfactual scenarios. (Sorrell, 2007)
The first one estimates the energy savings derived from the energy efficiency improvement. It aims to measure the energy consumption that would have been without the improvement. The second one isolates the RE. The goal is to determine the energy consumption that would have occurred after the improvement if there had been no behavioral adaption. (Sorrell, 2007) One of the biggest limits of this type of study is that exogenous factors can also have an impact on the demand for useful work and need to be taken into account.

On the other hand, econometric studies, are an indirect approach using secondary data. It incorporates proxy variables usually collected for other purposes but that can be used to measure the RE (Freire-González, 2011). Therefore, data on the demand for energy,

useful work, and energy efficiency are usually processed (Sorrell, 2007).
This type of study can be conducted at different levels of aggregation (household, region, country) and take several forms such as cross-sectional or time-series analysis (Sorrell, 2007). Nevertheless, as shown by a variety of papers such as Baležentis et al. (2021), energy demand for a variety of energy services such as heating or personal transportation tends to be income-inelastic and price-inelastic in developed countries.

**Studies**

A lot of studies have been conducted to estimate the RE. Those studies mainly focus on the direct RE, and the sectors studied are generally the transport or urban household sectors. That is due to the measurement difficulties mentioned before.

Concerning the household sector, in the United Kingdom, Chitnis and Sorrell (2015) estimated various RE with data from 1964 to 2013: 41% for domestic gas use, 48% for electricity, and 78% for fuels. More recently, Baležentis et al. (2021) carried out an econometric study on the household sector throughout the European Union. It highlighted a link between the level of economic development of a country and the RE. In low or middle-income country, the RE will be more likely to occur than in high-income state. Actually, the RE can be absent in high-income countries.

In the transport sector, Matos and Silva (2011) estimated that the direct RE for Portugal's road freight transport was about 24,1% from 1987 to 2006. Then, Wang et al. (2012) were interested in the direct RE induced by the transport of passengers in Hong Kong. Their work resulted in direct RE of 35% and 45% for the periods of 1993-2009 and 2002-2009 respectively. Also in the US aviation sector, Evans and Schäfer (2013) estimated a RE of 10% for 2005. In China, Zhang et al. (2017) concluded that the total $CO_2$ RE for private cars is between 30% and 35% during the sample period from 2001 to 2012. They also observed all types of RE (super conservation effect, partial RE, and BF) over that sample period.

To conclude, various studious tried to estimate the magnitude of the RE. Due to the estimation issues mentioned before, most of them focused on the direct RE. The evidence of RE was showed across various regions of the world for extensively studied sectors such as household and transport.

## 3.2 Traveling Purchaser Problem

To analyze the RE in transportation, we chose to study a specific optimization problem: the Traveling Purchaser Problem (TPP). In this section, this model representing a simple real-life business application will be described. In addition, the possible variants of the problem will be presented.

### 3.2.1 Problem Definition

The TPP is at the intersection of two types of problems that have been subject to many applications: procurement problems and routing problems.

In procurement problems, optimizing profits by maximizing revenues while minimizing costs is crucial. It aims to elaborate a purchasing plan in which the decision variables are the suppliers selected and the quantities ordered from each of these (Aissaoui et al., 2007). Satisfying the demand for a set of products or raw materials while minimizing the procurement costs is part of the daily life of many companies. This explains why those procurement problems are still mainstream nowadays (Manerba et al., 2017; Manerba, 2015).

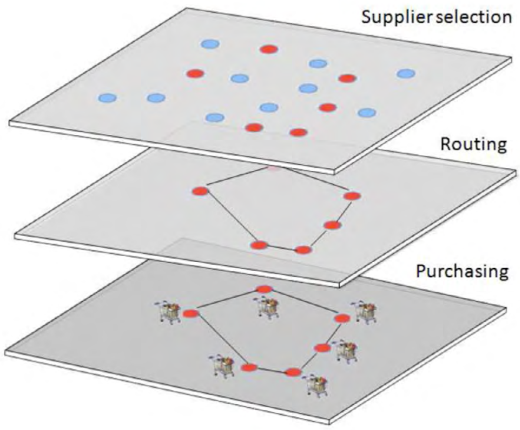



Figure 3.4: Components of the TPP in a layered structure (Manerba et al., 2017, p.2).

On the other hand, we can find the routing/transportation problems in which the objective is to optimize the traveling costs. In this case, the decision variables are the roads linking various geographical locations. The aim is to determine one or several optimal tours leaving a central depot, visiting all the nodes (suppliers, customers, etc.), and coming back to the starting location. The Vehicle Routing or the Traveling Salesman Problem (TSP) are examples of transportation problems (Manerba et al., 2017).

The great interest in the TPP is that it combines these aspects in one single model. It must deal at the same time with the selection of the suppliers, the quantities ordered from each of these, and the roads making up the vehicle tour. The purchaser must find an optimal purchasing plan while deciding the subset of suppliers he will visit on his tour. The objective function will therefore include both traveling and purchasing costs. One of the subtleties of TPP compared with the routing problems is that not all locations have to be visited necessarily. The decision to visit a supplier or not relies on the trade-off between the extra cost of traveling to it and the potential savings obtained in buying products at lower prices (Manerba et al., 2017).

### 3.2.2 Classification

As previously introduced, different variations of the TPP exist. The main variants will be presented below.

The first one distinguishes asymmetric and symmetric models. If the distance $d_{ij}$ between two suppliers $i$ and $j$ is different from $d_{ji}$, we are facing an Asymmetric Traveling Purchaser Problem (ATPP). However, in a Symmetric Traveling Purchaser Problem (STPP), $d_{ij} = d_{ji}$ for each arc $(i, j) \in A$ where $A$ is the set of Arcs. We can also call those variants directed and undirected TPP, respectively (Manerba et al., 2017; Choi and Lee, 2010).

Secondly, another criteria for the classification is related to the demand. The first possibility is to purchase one item of each product $k$ which means that $d_k = 1$, $\forall k \in K$. In this case, we denote the problem as a unitary demand case. However, in most of the applications, the demand for each product is a discrete positive value: $d_k > 0$, $\forall k \in K$ (Manerba et al., 2017; Gendreau et al., 2016).

Thirdly, the availability of the products at the suppliers can vary from one variant to another. The model is called Restricted-TPP (R-TPP) if the available quantity of a product $k \in K$ in a supplier $i \in M_k$ is defined as a real value $q_{ik}$. The latter can potentially be smaller than the product demand $d_k$. $M_k$ represents the sets of suppliers selected in the optimal routing tour. If the quantities offered by the suppliers are unlimited (i.e. $q_{ik} \geq d_k$, $\forall\, k \in K$, $\forall\, i \in M_k$), we call it Unrestricted-TPP (U-TPP) (Manerba et al., 2017; Gendreau et al., 2016; Choi and Lee, 2010).

Then, several distinctions can be made depending on the number of vehicles and their characteristics. If the company operates a fleet of vehicles instead of only one, we call it a Multiple Vehicle Traveling Purchaser Problem (MVTPP) (Bektas, 2006; Choi and Lee, 2010). Moreover, those vehicles could be limited by a certain capacity for freight transport. In this case, we would call the variant Capacitated TPP. The vehicle capacity can be also considered as unlimited and we would be facing an Uncapacitated TPP (Manerba et al., 2017; Fischetti et al., 2007). Furthermore, the fleet can be considered homogeneous if all the vehicles are identical or heterogeneous if not. Sometimes we can add an incompatibility constraint between products if they cannot be transported in the same vehicle (Manerba et al., 2017; Gendreau et al., 2016; Choi and Lee, 2010). Finally, we can also add a constraint ensuring that each vehicle does not exceed a certain distance traveled (Gendreau et al., 2016).

Afterwards, some differences exist according to the purchasing policy. We distinguish the split purchases from the non-split purchases. In a split variant, the demand for a product $k$ can be split between different vehicles. It means that multiple visits to a supplier are allowed. For instance, if a product is available at only one supplier, multiple vehicles can visit this node and transport the quantities instead of only one fulfilling the entire demand for this product $k$. The split version is a relaxed variant (Manerba et al., 2017).

Besides, in some applications, we can have multiple depots instead of only one. It means that vehicles can start their tour from one depot and end it either at the same location or at another depot. The former is defined as the fixed destination case while the latter is called the nonfixed destination variant (Bektas, 2006).

Finally, instead of fixing the number of vehicles, it is also possible to let the optimization problem decide which vehicles should compose the fleet. It is the fixed charges variant where each vehicle usually has an associated fixed cost. If a vehicle is part of the optimal solution, this fixed cost will be added to the total cost (Bektas, 2006).

To sum up, because of its great utility for modeling real-life business applications, several variations of the TPP were formulated through the literature.

## 3.3 Traveling Purchaser Problem and Rebound Effect

In the previous two sections, we presented the concept of RE as well as the TPP. One can wonder if these two topics have already been discussed together in the literature. To the best of our knowledge, only the article from Jaehn and Meissner (2022) combined these two concepts in a common study.

The authors modeled a Symmetric and Unrestricted TPP with a unitary demand for each product. The data were generated using random variables, except for the coordinates of the nodes composing the graph. The map included 40 cities from the Ruhr area in the western part of Germany. Besides, only one uncapacitated vehicle was used to purchase the products. Therefore, only the fuel efficiency of this vehicle varied from one iteration of the problem to another.

Concerning their research, they decided to vary the number of products and the product availability within the different suppliers to determine if those factors could influence the occurrence of potential RE. They concluded that RE, in particular BF, tends to be larger and more frequent with higher availability of products. Besides, they showed the existence of a relationship between the tour length and the magnitude of the RE that occurs. If the tour length is smaller the RE will be larger.

## 3.4 Conclusion

Before moving on to the next chapters of our thesis, it is important to summarize what we have highlighted in this chapter.

First, the RE can be classified either as direct or indirect RE. Direct RE represents the increase in demand caused by a lower energy cost while indirect RE refers to the consumer's increase in demand for other energy services, given that his income increases after an efficiency improvement (Greening et al., 2000). Besides, we noted that most of the studies focused on estimating direct RE. Indeed, estimating indirect RE is a real challenge given the number of confounding variables. That is why in this thesis we will focus our analysis only on direct RE.

After describing the RE, we detailed the TPP. As a reminder, we will use this model to analyze what drives the occurrence of RE. We noticed that a lot of variants of the problem exist, which means that a wide range of applications can be modeled. This is an advantage since it will allow us to test many variants of the problem. For example, we will vary the number of suppliers and the number of vehicles to analyze whether it can influence the occurrence of RE.

In the previous section, we mentioned the paper from Jaehn and Meissner (2022) that combined RE and TPP in a single study. Of course, we will differentiate our research from theirs. They decided to base their TPP on a specific node configuration from the western part of Germany and used a unitary demand for each product. In our case, the transportation network will not be the same for each instance of the problem and the product demands will be discrete positive numbers. It means that the optimizer will have to determine which quantities are bought at which supplier. In addition, they only modeled one single vehicle to purchase all the products while we will test multiple vehicles instances. Finally, additional variants of the problem will be tested in order to determine if it can influence the RE.

In conclusion, we will test plenty of variants of the TPP comparable to real-life cases. This will help us to answer our research question and to determine what parameters of those variants could influence the occurrence of direct RE.

# Chapter 4

# Model

In this chapter, the TPP that we will analyze later will be detailed. First, the mathematical formulation of the problem will be presented. Then, we will review the various methods and algorithms that can be used to solve a TPP, before presenting the one we chose. Finally, we will describe how to compute the RE in a transportation network.

## 4.1 Mathematical Formulation

This Traveling Purchaser Problem represents a situation where a decision-maker owns one or several vehicles and has to buy specific products. The latter can be purchased at various suppliers, each having its own price and capacity per product as well as a distance to the buyer's depot. The objective is to select and visit a subset of suppliers to satisfy the demand for each product while minimizing both purchasing and travel costs. We will determine the optimal tour of the vehicle(s) having a predefined capacity.

### 4.1.1 Assumptions

- The vehicle(s) starts and ends the route at the depot.
- The fuel price equals 1€/$l$. Therefore, fuel consumption and traveling cost are equal.
- If multiple vehicles are available, the split purchases are allowed. It means that the demand for each product can be split between the vehicles and that several trucks can visit the same supplier.

- The quantity purchased and transported can be a fractional number.
- Demand, and capacity of suppliers for each product are discrete positive values.
- Distances between each node are calculated based on the coordinates using Pythagorean theorem.
- It is possible to go from one node of the graph to any other node.
- The products are available at any supplier in varying quantities.
- For each product, the combined capacity of all suppliers exceed the total demand to satisfy.
- If several vehicles are available they all have the same capacity and the same fuel efficiency.
- The vehicle capacity is always a discrete positive value.

### 4.1.2 Sets and Indexes

Let $G = (V, E)$ be a complete graph where $V := \{1\} \cup M$ is the vertex set and $E$ the edge set. The vertex set combines a starting depot with index 1 and the set of suppliers $M = \{2, ..., n\}$. It includes the nodes of the transportation network. Each edge is represented as a pair of directed arcs $(i, j)$ and $(j, i)$.

- Set of Arcs $A := \{(i, j) : i \in V, j \in V, i \neq j\}$
- Set of Suppliers $M = \{2, ..., n\}$
- Set of Products $K = \{1, ..., b\}$
- Set of Vehicles $F = \{1, ..., g\}$

### 4.1.3 Parameters

- $c_{ik}$ : Unit purchasing cost [€/*unit*] of product $k$ from supplier $i$ $(i \in M; k \in K)$
- $d_{ij}$ : Distance [$km$] from node $i$ to node $j$ $((i, j) \in A)$

- $K_{ik}$ : Available capacity [*number of units*] of product $k$ at supplier $i$ ($i \in M; k \in K$)

- $f$ : Fuel efficiency of vehicles [$l/100km$]

- $d_k$ : Demand [*number of units*] for product $k$ ($k \in K$)

- $r$ : Capacity [*number of units*] of vehicle

### 4.1.4 Decision Variables

- $x^v_{ij}$ : Binary variable with $x^v_{ij} = 1$ if the route from node $i$ to node $j$ is used by vehicle $v$ and $x^v_{ij} = 0$ otherwise. ($(i, j) \in A; v \in F$)

- $y^v_i$ : Binary variable with $y^v_i = 1$ if node $i$ is visited by vehicle $v$ and $y^v_i = 0$ otherwise. ($i \in V; v \in F$)

- $z^v_{ik}$ : Variable representing the quantity of product $k$ purchased from supplier $i$ and transported by vehicle $v$. ($i \in M; k \in K; v \in F$)

- $u^v_i$ : Variable indicating the order of the corresponding node $i$ in the tour of vehicle $v$. ($i \in V; v \in F$)

- $w^v_{i,j}$ : Variable representing the quantities transported by vehicle $v$ from supplier $i$ to supplier $j$. ($(i, j) \in A; v \in F$)

### 4.1.5 Objective Function

$$\min C = \sum_{k\in K} \sum_{v\in F} \sum_{i\in M} c_{ik}\, z^v_{ik} + \sum_{v\in F} \sum_{(i,j)\in A} d_{ij}\, x^v_{ij}\, \frac{f}{100} \tag{4.1}$$

### 4.1.6 Constraints

- Flow constraints : for each supplier visited by vehicle $v$, two arcs must be selected.

$$\sum_{i\in A} x^v_{ij} = y^v_j \quad \forall\, j \in V, \quad \forall\, v \in F \tag{4.2}$$

$$\sum_{j\in A} x^v_{ij} = y^v_i \quad \forall\, i \in V, \quad \forall\, v \in F \tag{4.3}$$

– Supplier capacity constraint: purchased quantities by each vehicle $v$ cannot exceed the capacity of supplier $i$ for product $k$. Besides, there must be no quantity purchased if the supplier is not visited by the vehicle.

$$z_{ik}^{v} \leq K_{ik}\, y_i^v \quad \forall\, v \in F\,, \quad \forall\, k \in K\,, \quad \forall\, i \in M \tag{4.4}$$

– Availability of suppliers quantities : the total quantities for a product $k$ transported by the fleet of vehicles cannot exceed the capacity of the supplier $i$ for this product

$$\sum_{v \in F} z_{ik}^{v} \leq K_{ik} \quad \forall\, i \in M\,, \quad \forall\, k \in K \tag{4.5}$$

– Demand constraint: The demand for each product $k$ should be equal to all the quantities purchased and transported by the fleet of vehicles.

$$\sum_{v \in F} \sum_{i \in M} z_{ik}^{v} = d_k \quad \forall\, k \in K \tag{4.6}$$

– Vehicle capacity constraint: For each vehicle $v$, the total ordered quantities cannot exceed the minimum between the capacity of the vehicle (denoted $r$) and the total demand ($\sum_{k \in K} d_k$).

$$\sum_{k \in K} \sum_{i \in M} z_{ik}^{v} \leq min\{r, \sum_{k \in K} d_k\} \quad \forall\, v \in F \tag{4.7}$$

– Subtour elimination constraint (Miller-Tucker-Zemlin Formulation): If vehicle $v$ drives from node $i$ to node $j$ (i.e. $x_{ij}^v = 1$) , the constraint will make sure that $u_j^v$ is always larger than $u_i^v$ . By fixing the first node as depot (i.e. $u_1^v = 1$) for each vehicle, all the subtours will be eliminated.

$$u_i^v - u_j^v + (n-1)\, x_{ij}^v \leq n-2 \quad \forall v \in F \;\; \forall\, (i,j) \in A, \;\; j \in V\backslash\{1\} \tag{4.8}$$

$$u_i^v \leq n\, y_i^v \quad \forall i \in V\backslash\{1\}, \; \forall v \in F \tag{4.9}$$

– Subtour elimination constraint : The tour of each vehicle $v$ starts at the depot (i.e. node 1)

$$u_1^v = 1 \;\; \forall\, v \in F \tag{4.10}$$

– Flow constraint for quantities : the quantities transported by a vehicle $v$ when it leaves a supplier $i$ are equal to the quantities purchased from that supplier $i$ plus the quantities the vehicle $v$ was already transporting before.

$$\sum_{j \in M} w_{j,i}^v + \sum_{k \in M} z_{i,k}^v = \sum_{j \in M} w_{i,j}^v \;\; \forall i \in M, \; \forall v \in F \tag{4.11}$$

– Big-M constraint: no quantities can be transported on the arc $(i,j)$ if the vehicle $v$ is not taking this arc. The big-m parameter will always be the minimum between the capacity of the vehicle denoted $r$ and the total demand $\sum_{k \in K} d_k$.

$$w_{i,j}^v \leq \; min\{r, \sum_{k \in K} d_k\} \;\; x_{i,j}^v \;\; \forall v \in F, \; \forall (i,j) \in A \tag{4.12}$$

– First node constraint: no quantities can be transported from the depot to the first node visited since no quantities have been bought yet.

$$w_{1,j}^v = 0 \;\; \forall v \in F, \; \forall j \in A \tag{4.13}$$

– Last node constraint: the total quantities brought back by the entire fleet of vehicles at the end of their tour is equal to the total demand.

$$\sum_{i \in A} \sum_{v \in F} w_{i,1}^v = \sum_{k \in K} d_k \tag{4.14}$$

– Variable definition constraints:

$$x_{ij}^v \in \{0,1\} \;\;\; \forall\, (i,j) \in A\,, \;\; \forall v \in F$$

$$\mathrm{y}_i^v \in \{0,1\} \;\;\; \forall\, i \in M, \quad \forall\, v \in F$$

$$\mathrm{z}_{ik}^v \geq 0 \;\; \forall\, k \in K, \;\; \forall\, i \in M, \;\; \forall\, v \in F$$

$$\mathrm{u}_{ij}^v \geq 0 \;\; \forall (i,j) \in A\,, \;\; v \in F$$

### 4.1.7 Formulation Discussion

As it will be detailed later, our objective will be to compare different instances of the TPP to determine what drives the occurrence of RE. Therefore, we had to find a formulation that was able to solve problems of reasonable size in a decent time. Solving very large instances of the problem, or finding a stronger formulation than the one presented is not within the scope of this thesis. Besides, constraints 4.8 to 4.10 are not essential to ensure the feasibility of the solution since constraints 4.11 to 4.14 are already preventing subtours. However, they will considerably facilitate the interpretation of the results and that is why we decided to keep them in our model. Indeed, the $u_i^v$ variables indicate the order of the corresponding node $i$ in the tour of vehicle $v$. In the next chapters, we will compare the vehicle tours before and after an efficiency improvement. As a result, these variables will save us a lot of time in retrieving the optimal tour of each vehicle.

## 4.2 Solution Approach

### 4.2.1 Problem Properties and Complexity

The TPP has been one of the most investigated generalizations of the Traveling Salesman Problem (TSP). Indeed, it combines three specific problems: supplier selection, routing construction, and product purchasing planning. Therefore, because of its computationally challenging aspect, but also its possible application to real-life problems, the TPP attracted the attention of both researchers and practitioners. (Manerba et al., 2017)
Before reviewing what methods and algorithms are used to solve TPP instances, it is important to understand the actual complexity behind the problem.
In fact, the TPP is what researchers call a $NP$-Hard problem. $NP$-Hard (non-deterministic-polynomial-time) problems are distinguished from $NP$ problems and $P$ problems.
$P$ Problems can be solved to the optimum by an algorithm that needs a number of operations that grows polynomially with the size of the problem (Van Vyve, 2020). Then, $NP$ problems is a class of problems for which an answer can be verified in a polynomial time. On the other hand, a problem is NP-hard if solving it in polynomial time would imply that any problem in $NP$ could be solved in polynomial time as well.

The $NP$-hardness of the TPP can be proven this way: the TPP is a generalization of both the TSP and the Uncapactited Facility Location Problem (UFLP), which are $NP$-hard problems themselves (Manerba et al., 2017).
In consequence, different algorithms were studied to solve the TPP (Hamdan et al., 2017). We will differentiate between exact solution approaches and heuristics algorithms. For each method, a brief explanation will be given, as well as an example of results obtained in terms of the kind and size of the problems solved.

### 4.2.2 Exact Solution Approaches

In order to obtain exact solutions to TPP, Branch-and-bound (B&B) approaches were implemented. These are the basic or general algorithms for solving Mixed Integer Linear Program (MILP) (Pochet and Wolsey, 2006). The algorithm solves the relaxation[1] of a series of sub-problems where some variables are fixed. The goal is to find the optimal solution by solving as few problems as possible and prove that no other feasible solution is better than the optimal solution found. (Van Vyve, 2020)

The first B&B to solve the TPP was proposed by Singh and van Oudheusden (1997). Their intuition was to split the set of all feasible tours into smaller subsets. For each of those, a lower bound on the sum of traveling and procurement costs were computed. The developed algorithm can be used to solve instances of symmetric TPP with up to 20 nodes and 30 products in a reasonable time.

Later on, branch-and-cut techniques enabled substantial advancement in the size of problems solved to optimality. The Branch-and-cut (B&C) is a B&B algorithm that uses cutting planes, i.e. additional constraints added to strengthen the linear relaxation (Pochet and Wolsey, 2006). Riera-Ledesma and Salazar-González (2006) used a B&C algorithm to solve asymmetric instances of the TPP with up to 200 nodes and 200 products.

[1]The linear relaxation of a MILP is obtained by dropping the integrality constraints to transform the problem into a Linear Program (LP) that can be solved. The resulting optimization problem has a larger feasible region and a smaller objective function. If the relaxation leads to an optimal solution that is feasible in the original problem and for which the relaxed objective function is the same as the original, then this solution is also the optimal solution to the original problem.(Van Vyve, 2020)

### 4.2.3 Heuristics Algorithms

Heuristics can be used to find a solution to a large problem that cannot be solved to optimality. These are algorithms that output a solution that is not guaranteed to be optimal (Van Vyve, 2020). These may be useful when the B&C algorithm is too slow or takes a long time to find good feasible solutions (Pochet and Wolsey, 2006).
We will explore constructive heuristics, local search heuristics, and meta-heuristics.

Constructive heuristics create a solution starting from an empty solution. Regarding the TPP, all constructive heuristics rely on the concept of saving to measure the convenience in terms of decrease in total cost when adding a new supplier to the solution (Manerba et al., 2017).
Golden et al. (1981) developed the first saving algorithm for the TPP called Generalized Savings Heuristic. It is a greedy procedure that at each iteration, adds the most convenient supplier to the current visiting cycle. Other constructive heuristics include Tour Reduction Heuristic, Commodity Adding Heuristic, and Market Adding Heurisitc (Ong, 1982; Pearn, 1991; Laporte et al., 2003).

Next, local search heuristics are iterative algorithms that continuously seek to improve a solution. A neighborhood $N(S)$ of any solution $S$ is defined. Neighbors of $S$ are obtained by either removing an element from S, adding an element to $S$, or switching one element in $S$ with one not in $S$. Therefore, at each iteration, all neighboring solutions of the current solution are checked. If a better solution is found, the current solution is updated. If not, the algorithm stops. (Van Vyve, 2020)
Voß (1996) formalized the Generalized Savings Heuristic and the Tour Reduction Heuristic as local search based on the addition and the deletion of a supplier, respectively. Riera-Ledesma and Salazar-González (2005) proposed a heuristic-based approach using a special neighborhood definition.

Finally, a metaheuristic is a master strategy guiding one or more heuristics to find solutions beyond local optimality (Manerba et al., 2017). These usually do not give any guarantee about the quality of the solution obtained (Van Vyve, 2020). Examples of metaheuristics include Genetic Algorithm, Tabu Search, and Ant Colony. Bernardino and Paias (2018) proposed metaheuristics for the uncapacitated TPP by combining three genetic algorithms with a local search.

### 4.2.4 Chosen Method

To be able to answer our research question, we had to choose a method that would allow us to obtain the optimal solution. As part the methodology that will be explained later, we will compare the optimal solutions of various instances in order to determine what drives the occurrence of RE. Thus, using heuristics or metaheuristics algorithms was not an option since they do not guarantee the optimal solution. We would not have been able to compare the results properly or to draw any valid conclusions.

That is why we implemented the mathematical formulation presented in Section 4.1 in the software AIMMS that uses the CPLEX 20.1 optimization package from IBM ILOG. For MILP, CPLEX uses a B&C algorithm as well as dynamic search. The latter is based on the B&C and is a proprietary method from IBM ILOG. We let the search strategy parameter to "Automatic", which means that the solver decides what algorithm to use to solve the problem. Nevertheless, according to IBM, for many models, dynamic search finds feasible and optimal solutions quicker than the traditional B&C algorithm. Besides, CPLEX automatically decides whether or not to perform pre-solving and probing[2]. Then, it uses the Dual Simplex algorithm on each sub-problems. Finally, when proceeding back through the tree when a node is infeasible or cut off, CPLEX uses the Best-Bound strategy, choosing the node with the best objective function for the associated LP relaxation.

[2]Probing is a technique that looks at the logical implications of fixing each binary variable to 0 or 1. It is performed after preprocessing and before the solution of the root relaxation.

## 4.3 Computing the Rebound Effect in a Transportation Network

In transportation networks, direct RE may occur after a fuel efficiency improvement of the vehicles. Since the fuel consumption per kilometer would be reduced, the optimized solution could be to buy products at lower prices from more distant suppliers. A trade-off between traveling costs on the one hand and purchasing costs, on the other hand, would apply. To compute the RE that could occur, we used the following formula (Jaehn and Meissner, 2022; Stern, 2020):

$$RE = 1 - \frac{Actual\ Savings}{Potential\ Savings}$$

As a reminder, "Actual savings" represents the savings that actually happen after the fuel efficiency improvement. In parallel, "Potential savings" are the savings expected based on the idea that people will drive the same distance as if there was not any fuel efficiency improvement.

In our model, the RE can result in an increase in the distance traveled by the vehicles following an improvement in fuel efficiency. Therefore, the total distance traveled by all the vehicles denoted $D^*(f)$ will depend on the Fuel Efficiency $(f)$ *[l/100 km]* and can be computed as follow :

$$D(f) = \sum_{v \in F} \sum_{(i,j) \in A} d_{ij} \frac{x_{ij}^v(f)}{100}$$

To compare the distance traveled before and after the energy improvement, we will denote $f^0$ and $f^n$. Indeed $f^0$ represents the fuel efficiency before the improvement while $f^n$ is the fuel efficiency after (i.e. $f^0 > f^n$). Those notations are used to distinguish the total distance traveled before the efficiency improvement denoted $D^0$ from the total distance traveled after it $D^n$ :

$$D^0 = D(f^0)$$

$$D^n = D(f^n)$$

One of the assumptions of our model is that the fuel price equals 1. This means that the fuel consumption and traveling costs coincide. This will facilitate the analysis as well as the interpretation of the results. Therefore, they can be written as :

$$Fuel\ Consumption = Traveling\ costs = \frac{D(f)\, f}{100}$$

We can now combine those notations with the RE formula where the savings can be either considered as fuel consumption savings or traveling costs savings :

$$RE(f^0, f^n) = 1 - \frac{D^0\, f^0 - D^n\, f^n}{D^0\, f^0 - D^0\, f^n}$$

The distance traveled values between each change of $f$ are considered to have been made in equilibrium states. Indeed, in reality, it would take some time for the situation to stabilize after such a fuel efficiency change.

The RE classification used is :

- RE = 0 : There is no rebound effect because the "Potential savings" have been achieved as expected. In other words, "Actual savings" and "Potential savings" are equal.
- 0 < RE $\leq$ 1 : We are facing a partial rebound effect. The energy savings by improving energy efficiency are partially offset.
- RE = 1 : There is no energy savings because there are fully offset. This is the full rebound effect case.
- RE > 1 : An increase in energy consumption takes place after the fuel efficiency improvement. This is called a backfire.

# Chapter 5

# Data

In this chapter, we will explain the reasons why we generated artificial data to analyze the occurrence of RE in the TPP. Then, we will detail how we generated those data.

To begin, it is important to remind that our thesis aims to understand what parameters of the TPP drive the occurrence of the RE.
Solving only one instance of a problem was never an option since we are not interested in quantifying the size of RE. Our goal is to analyze a large amount of TPP instances with different properties in terms of the number of nodes, suppliers, products, etc. Nevertheless, to the best of our knowledge, such real-world data are not available in sufficient quantity. In addition, benchmark datasets with a large number of instances exist for TPP. However, they do not actually represent real-life applications and are mostly created to analyze the performance of the algorithms, which is not within the scope of our thesis.
That is why we decided to generate our own artificial data. On the one hand, this will allow for more flexibility in terms of testing and the possibility to investigate the effect of different variants and parameters. Not only we can generate additional suppliers, products, or vehicles to evaluate the impact on the occurrence of RE but we can also change the way those data are generated to explore the effects of input data on the results. On the other hand, we will avoid drawing conclusions from specific node configuration, prices, or supplier capacities that could impact drastically our results.

For each instance of the problem, the coordinates of every node were generated randomly using a uniform distribution $\mathcal{U}(1, 500)$. Indeed, the idea was to represent a 500 $km$ by

500 *km* map. The first node was arbitrarily chosen to be the depot while the remaining nodes represented the suppliers. In order to generate instances similar to real-life cases, the position of the depot was also randomly generated. As a result, it could either be located near the center of the map or in a corner. Eventually, the distance matrix was built by calculating the euclidean distance between each node. An example of a network with 10 notes is illustrated in Figure 5.1.

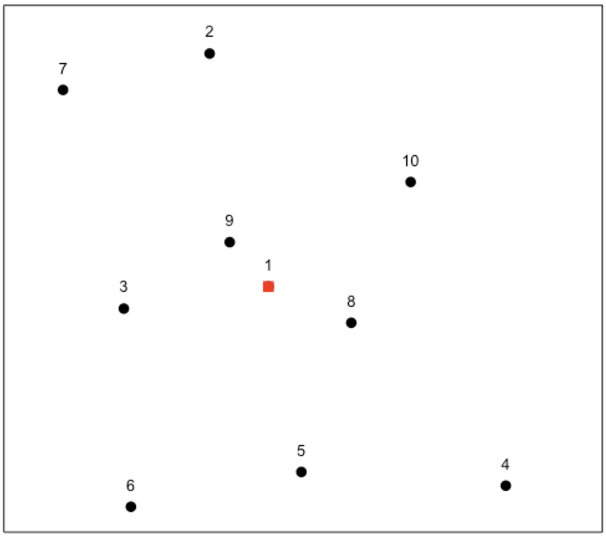



Figure 5.1: Illustration of a network with 10 nodes.
The depot is represented in red.

In addition, to create a balance between procurement costs and travel costs that allows for occurrences of RE, the unit purchasing cost of each product from each supplier was calculated based on this formula: $c_{i,k} = \frac{Num_k}{d1,j}$ $\forall k \in K, \ \forall j \in M$ where $Num_k$ is an arbitrary number that depends on the product type and that was generated using a uniform distribution $\mathcal{U}(500, 2000)$. The idea here is that suppliers located far away from the depot ($i = 1$) should offer a lower price and that prices should vary from one product to another. Besides, the demand for each product was also generated using a uniform distribution: $d_k = \mathcal{U}(20, 100)$ $\forall k \in K$. You can observe the demand and purchasing prices generated for the example of 10 nodes and 3 products in Tables 5.1 and 5.2.

| Product | Demand [units] |
|---|---|
| 1 | 87 |
| 2 | 85 |
| 3 | 31 |

Table 5.1: Example of generated demand.

| | Product | | |
|---|---|---|---|
| Node | 1 | 2 | 3 |
| 1 | - | - | - |
| 2 | 4,57 | 7,34 | 5,45 |
| 3 | 7,09 | 11,39 | 8,45 |
| 4 | 3,43 | 5,52 | 4,09 |
| 5 | 4,93 | 7,93 | 5,88 |
| 6 | 3,72 | 5,97 | 4,43 |
| 7 | 3,9 | 6,27 | 4,65 |
| 8 | 12,05 | 19,36 | 14,36 |
| 9 | 20,15 | 32,37 | 24,01 |
| 10 | 7,08 | 11,38 | 8,44 |

Table 5.2: Example of generated unit purchasing costs [€/unit].

Furthermore, we make the assumption that all the vehicles used are freight trucks. As a result, the fuel efficiency $f$ is equal to 40 *l/100km* (Statista, 2019). Concerning the fuel price, it is equal to 1€/$l$. It means that fuel consumption and traveling costs are equivalent. This assumption will facilitate the analysis in the next sections.

Finally, suppliers' capacities were also randomly generated using a normal distribution $K_{ik} \sim \mathcal{N}(\frac{2d_k}{n}, \frac{2d_k}{4n})$ where $d_k$ is the demand for product $k$ and $n$ is the number of suppliers. By doing this, all the products could be available at each supplier but in varying quantities. In Table 5.3 we can find the capacities generated for the same example we mentioned before.

| | Product | | |
|---|---|---|---|
| Node | 1 | 2 | 3 |
| 1 | - | - | - |
| 2 | 19 | 17 | 7 |
| 3 | 18 | 19 | 6 |
| 4 | 13 | 28 | 8 |
| 5 | 19 | 18 | 11 |
| 6 | 22 | 16 | 7 |
| 7 | 21 | 12 | 8 |
| 8 | 7 | 17 | 4 |
| 9 | 19 | 14 | 9 |
| 10 | 20 | 22 | 7 |

Table 5.3: Example of the Capacities generated for each supplier [units].

# Chapter 6

# Numerical Application & Testing Methodology

In this chapter, we will deeply analyze a numerical application of our model. We will explain the results obtained and compute the potential RE that could occur. Furthermore, we will describe in detail the methodology that will be used in Chapter 7.

## 6.1 First Numerical Application

For this first numerical application of the problem, the network is composed of 10 nodes. The first one is the depot, while the 9 others are the suppliers. Furthermore, only one vehicle with a fuel efficiency of 40 *l/100km* is used to procure a single product. The data of the different parameters such as the demand, the capacity, and the unit purchasing cost of each supplier are generated as mentioned in Chapter 5. The data generated for this numerical application are presented in Table 6.1.

In addition, a demand of 41 units has been generated, and the vehicle capacity in this case is sufficient for the problem to be feasible.

| Node | Capacity [units] | Unit Purchasing Cost [€/unit] |
|---|---|---|
| 1 | - | - |
| 2 | 10 | 8,14 |
| 3 | 8 | 2,93 |
| 4 | 12 | 1,87 |
| 5 | 8 | 2,72 |
| 6 | 10 | 4,81 |
| 7 | 5 | 1,99 |
| 8 | 9 | 1,76 |
| 9 | 9 | 3,41 |
| 10 | 9 | 5,99 |

Table 6.1: Capacity and unit purchasing cost for each supplier.

We implemented the formulation presented in Chapter 4 in the optimization software *AIMMS* that uses the CPLEX 20.1 solver from IBM ILOG. As a result, we were able to get the optimal solution that minimizes the sum of the procurement and traveling cost. Figure 6.1 depicts the optimal tour of the vehicle for this numerical application.

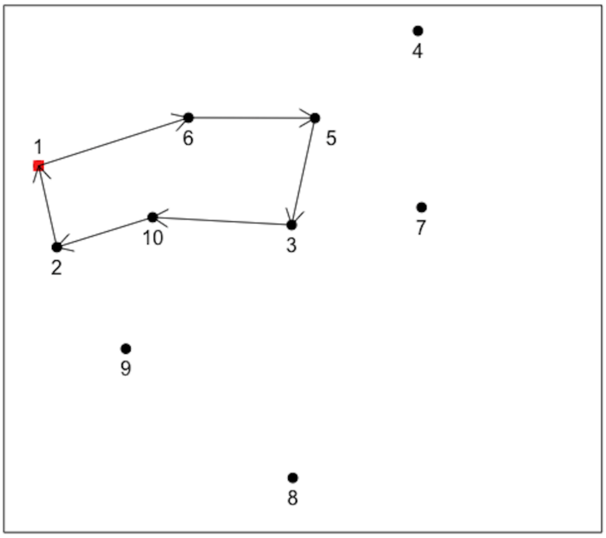



Figure 6.1: Optimal vehicle tour with a fuel efficiency of 40 *l/100km*.
The depot is represented in red.

We tend to procure the product from the nearest suppliers even if they offer a higher price. However, it might be interesting to buy the product from more distant suppliers such as suppliers 4 or 8, who offer larger quantity at lower price.

One question can be raised: How would the trade-off between procurement cost and traveling cost be impacted by the efficiency improvement of the vehicle? Indeed, with an increase in fuel efficiency, it would be optimal to either source the product from the same set of suppliers and therefore reduce the transportation cost, or select another set of cheaper suppliers to benefit from better prices.

To answer this, we will solve this instance of the problem 10 times with different values of the fuel efficiency ($f$). For clarity, each resolution of the problem with a different $f$ will be called iteration and will be numbered from 1 to 10. At each iteration, the fuel efficiency will be improved by 10%[1] compared to the previous one. For example, the vehicle of the second iteration will have a fuel efficiency equals to 36 *l/100km*. This method will help us to understand if the optimal vehicle tour would change if a more efficient vehicle is used. Table 6.2 summarises the key measures for the 10 iterations of the numerical example.

| Iteration | Fuel Efficiency [$l$/100 km] | Transport Cost [€] | Procurement Cost [€] | Total Cost [€] | Traveled Distance [km] | RE [%] |
|---|---|---|---|---|---|---|
| 1 | 40,00 | 268,37 | 196,05 | 464,42 | 670,93 | - |
| 2 | 36,00 | 241,54 | 196,05 | 437,59 | 670,93 | 0% |
| 3 | 32,40 | 275,34 | 133,71 | 409,05 | 849,82 | 239,96% |
| 4 | 29,16 | 247,81 | 133,71 | 381,52 | 849,82 | 0% |
| 5 | 26,24 | 223,03 | 133,71 | 356,74 | 849,82 | 0% |
| 6 | 23,62 | 217,63 | 116,07 | 333,70 | 921,40 | 75,81% |
| 7 | 21,26 | 195,87 | 116,07 | 311,94 | 921,40 | 0% |
| 8 | 19,13 | 176,28 | 116,07 | 292,35 | 921,40 | 0% |
| 9 | 17,22 | 158,65 | 116,07 | 274,72 | 921,40 | 0% |
| 10 | 15,50 | 142,79 | 116,07 | 258,86 | 921,40 | 0% |

Table 6.2: Key measures for the 10 iterations of the numerical example.

First, by looking at Table 6.2 above, we notice that the total cost decreased by 26,83€ from iteration 1 to iteration 2. This can be explained by the fact that the vehicle tour did not change while the efficiency of the vehicle was improved. The same suppliers were selected and the same distance was driven. In other words, the same decisions as in iteration 1 have been taken, which resulted in a decrease in transport cost.

[1]We are conscious that the choice of a 10% incrementation will influence the magnitude of the computed RE. Indeed, an incrementation closer to 0 would mean that a very small improvement in energy efficiency could possibly lead to an increase in the total traveled distance. In this case, the RE would be either 0 or close to infinity. However, setting this incrementation to 10% and not changing it during the whole experimentation process implies that it will be possible to compare results from different instances of the problem, which is the main goal of our analysis. As a result, the choice of the incrementation value will not have a significant impact on our conclusions.

In addition, because we assume that fuel price equals to 1, transport cost coincide with fuel consumption. Therefore, less fuel was consumed and potential savings resulting from the increase in efficiency have been achieved as expected. No RE occurred.

Then, if we have a look at the distance traveled by the vehicle over the 10 iterations, we can see that it increased twice and both times a RE occurred. The first time is when the efficiency increased from 36 to 32,4 *l/100km* between the iterations 2 and 3. A BF of 239,96% happened. In order to better understand the mathematical intuition behind this, here is how it was computed :

$$\begin{aligned} RE(f^2, f^3) &= 1 - \frac{D^2\,f^2 - D^3\,f^3}{D^2\,f^2 - D^2\,f^3} \\ &= 1 - \frac{670,93 \times 36 - 849,82 \times 32,4}{670,93 \times 36 - 670,93 \times 32,4} = 239,96\% \end{aligned}$$

The improved efficiency of the vehicle caused a change in decision. The vehicle tour is obviously different. It is now optimal to travel further and buy products from cheaper suppliers. Instead of reducing the distance traveled and thus the fuel consumption, the opposite took place.

As a reminder, in the first iteration, we were visiting supplier 2 who offers the highest price, with a unit purchasing cost of 8,14€. As we can see in Figure 6.2, we are now buying 12 units from supplier 4 at a unit purchasing cost of 1,87€. As a matter of fact, the procurement cost decreased unlike the traveling cost.

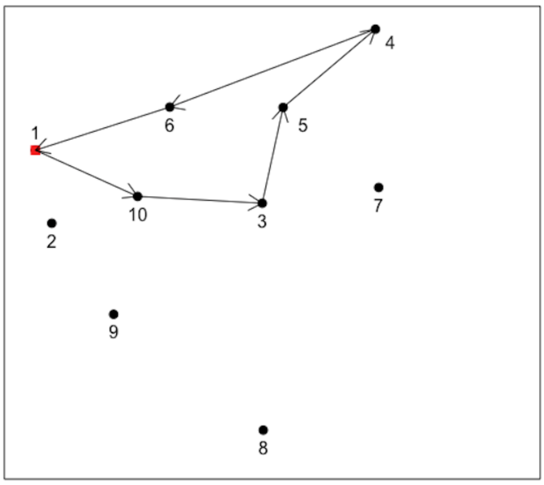



Figure 6.2: Optimal vehicle tour with an efficiency of 32,4 *l/100km*
BF of 239,96%.

The second time the distance increased was between iterations 4 and 5. A partial RE of 75,81% was observed. It means that the energy savings expected from the energy efficiency improvement were partially offset due to the new decisions taken. From Figure 6.3, we notice that visiting supplier 7 is now part of the optimal solution since he offers a price of 1,99€. We also note that supplier 10, who offers the second-highest unit cost, is not visited anymore.

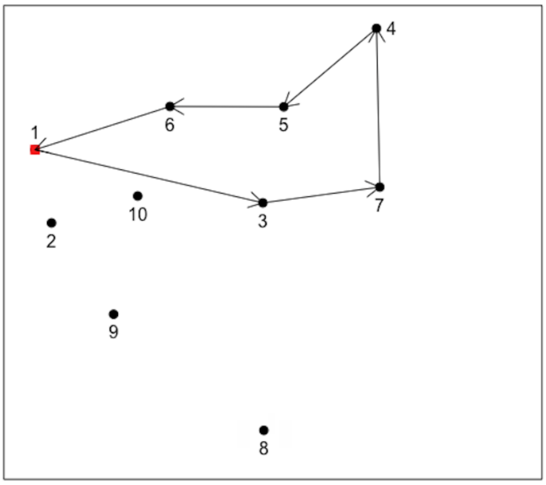



Figure 6.3: Optimal vehicle tour with an efficiency of 23,6 *l/100km*
. Partial RE of 75,81%.

Finally, we decided to plot two graphs to gain a better understanding of what is happening when a RE or BF occurs. By looking at Figure 6.4, we can see that the total traveled distance increased at each iteration where a RE or a BF occurred.

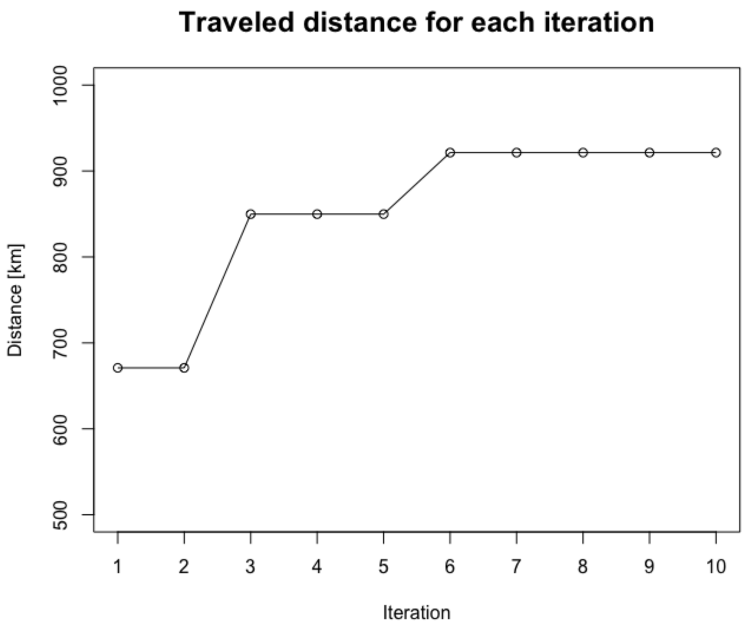



Figure 6.4: Traveled distance for each iteration.

In addition, Figure 6.5 compares the actual fuel consumption at each iteration with the potential fuel consumption that could have arisen without any change in the decision-making process. If we take a closer look at iteration 3, we see that an increase in fuel consumption took place after the efficiency improvement, and therefore, a BF occurred. On the other hand, between iterations 5 and 6, the fuel consumption decreased but part of the potential savings due to the efficiency improvement was offset by the change in decision-making that induced a longer traveled distance.

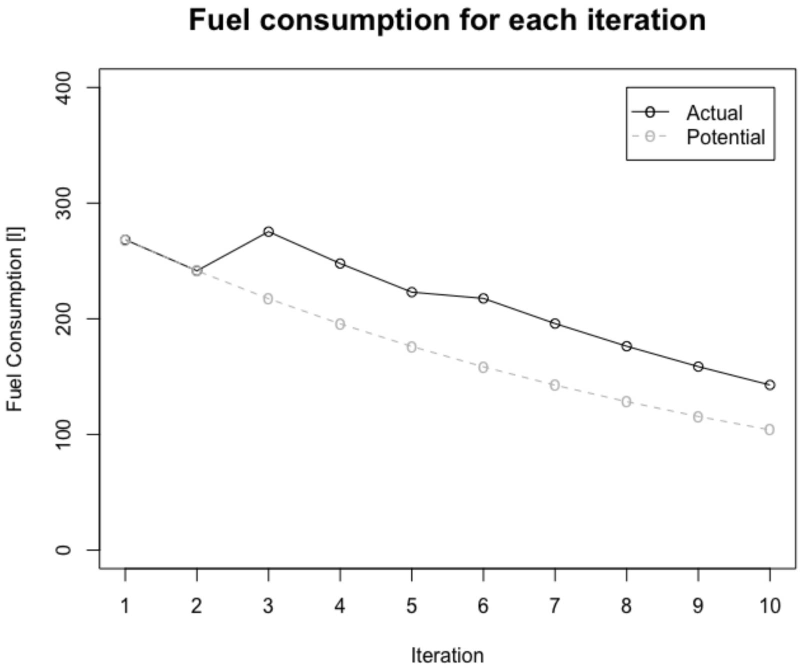



Figure 6.5: Fuel consumption for each iteration.

In conclusion, two RE, including one BF, occurred for this instance of the problem with the following characteristics: 10 nodes, one product, and one vehicle. Of course, one can argue that the coordinates of the nodes and other parameters such as the capacity of suppliers might have caused the occurrence of RE. That is the reason why we decided to generate 10 instances of this problem with different coordinates, purchasing cost, demand, and capacities. It means that these 10 instances will have the same characteristics (i.e. 10 nodes, one product, and one vehicle) but will differ according to the demand, suppliers' capacity, unit purchasing costs, and node coordinates that were newly generated.

Then, as we did before, for each of the 10 instances, we will vary the fuel efficiency by 10% and compute the eventual RE.

By generating these 10 instances of the same problem configuration, we will avoid drawing conclusions that could be the consequence of a specific data generation. Finally, we will retrieve how many RE and BF appeared on average when we improve 10 times the fuel efficiency by 10%.

| Instance | # RE | # BF |
|---|---|---|
| 1 | 1 | 1 |
| 2 | 0 | 0 |
| 3 | 0 | 0 |
| 4 | 2 | 1 |
| 5 | 1 | 0 |
| 6 | 2 | 2 |
| 7 | 0 | 0 |
| 8 | 0 | 0 |
| 9 | 0 | 0 |
| 10 | 1 | 1 |
| Average | 0,7 | 0,5 |

Table 6.3: Example of output for 10 generated instances with 10 nodes, one product and one vehicle.

Table 6.3 illustrates the output obtained for 10 generated instances with 10 nodes, one product and one vehicle. As a side note, instance 4 corresponds to the numerical application we analyzed in details. We notice that, on average, we observe 0,7 RE and 0,5 BF per instance.

## 6.2 Testing Methodology

As a reminder, we want to determine what drives the occurrence of RE and BF. To do so we base our analysis on a TPP that exists under multiple variants that we presented in Chapter 3.

In Chapter 7, we will experiment with multiple variations of the TPP to understand to what extent certain characteristics can impact the occurrence of potential RE. Indeed, we want to vary:

- The number of nodes in the network.
- The number of products to source.

– The number of vehicles available to source the product(s).

– The total traveled distance that can be subject to a distance-traveled tax.

– The number of products considered as exclusive which means available at only one supplier.

We will apply the methodology used in the numerical application to retrieve the number of RE and BF that occur on average when we improve the fuel efficiency 10 times. Below is a summary of this methodology.

**Step 1:** Decide what characteristic of the problem we want to vary.
**Step 2:** Generate a first instance of this specific problem.
**Step 3:** Solve 10 iterations of this instance with different values of $f$. Starting from 40 *[l/100km]*, the fuel efficiency will improve by 10% between each iteration.
**Step 4:** Compute the RE that occurs between each iteration and report the total number of RE and BF.
**Step 5:** Repeat Step 2 to 4 for 9 other generated instances of this specific problem.
**Step 6:** Compute the average number of RE and BF per instance.
**Step 7:** Compare the results obtained to understand the influence of this characteristic on the occurrence of RE and BF.

For instance, we could compare our first numerical application with two others where only the number of nodes will differ (i.e 5 nodes and 15 nodes). Ten instances of each will be generated to compute the average RE and BF per instance. In conclusion, we will end up with two tables similar to Table 6.3 but one for the problem with 5 nodes and the other one with 15 nodes. It will then be possible to compare the results and determine whether the number of nodes influences on the occurrence of RE and BF.

# Chapter 7

# Experimentations & Results

In this chapter, the methodology presented previously will be applied to understand what drives the RE in our TPP. We will therefore analyze the impact of the number of nodes, products, and vehicles on the occurrence of RE and BF. The implementation of a distance-traveled tax and the exclusive availability of products will also be discussed.
Finally, the last section of this chapter will focus on using statistical methods to summarise and confirm the obtained results.

## 7.1 Nodes

This first experiment consisted in varying the number of nodes to find out if it impacts the occurrence of RE and BF. To do so, one vehicle will be used to procure a single product. We then applied the methodology described in Chapter 6 to retrieve data from problems with 3, 5, 7, 10, 15, 20, 25, 30 and 35 nodes.

From Figure 7.1, we can analyze the average occurrence of RE and BF. On the one hand, we noticed that the number of RE tended to increase with the number of nodes. On the other hand, the trend was not the same for BF. Indeed, for instances with 3, 5 and 7 nodes, the black curve and the red curve merge on the graph. This means that each time a RE occurred, it was actually a BF. For 10 nodes and more, the two curves separate. The number of RE increased while the number of BF remained more or less constant regardless of the number of nodes in the network. It must therefore be understood that partial RE appeared more often when the number of suppliers increased.

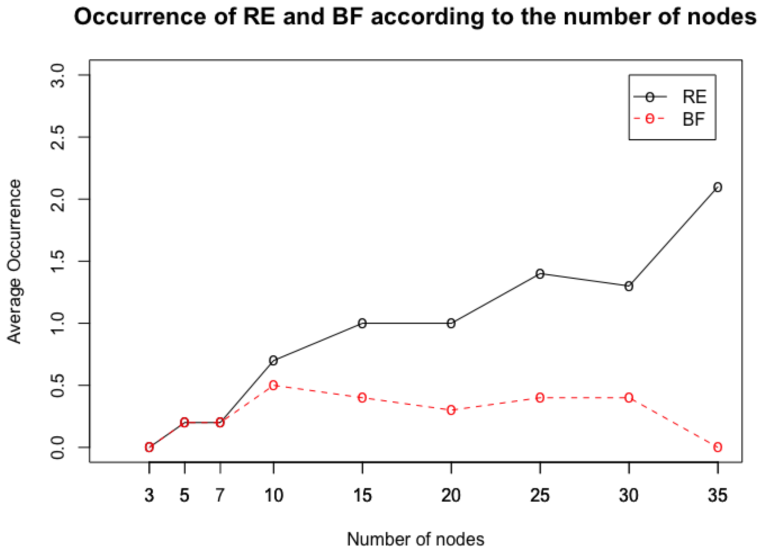



Figure 7.1: Average occurrence of RE and BF per instance according to the number of nodes.

On the second graph (Figure 7.2), the average Rebound size as a function of the number of nodes in the transportation network is depicted. First, we immediately noticed that, for instances with 5 and 7 nodes, tremendous BF have occurred. Then, when the number of nodes increased, the average RE size decreased. Indeed, when at least 20 nodes were present on the map, the average Rebound size was always under 100%. It should also be noted that no RE was detected for instances with only 3 nodes.

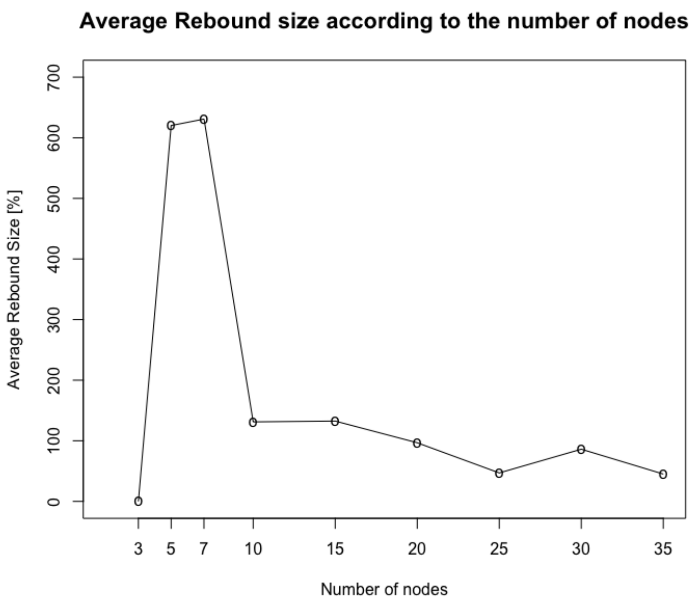



Figure 7.2: Average Rebound size according to the number of nodes.

Next, we analyzed the distribution of the RE sizes that appeared among the 10 instances generated with 35 nodes. This is represented as a histogram in Figure 7.3. In total, out of the 22 RE that occurred, all of them were under 100% with a most frequent value located around 45%. As mentioned before, only partial Rebound were detected.

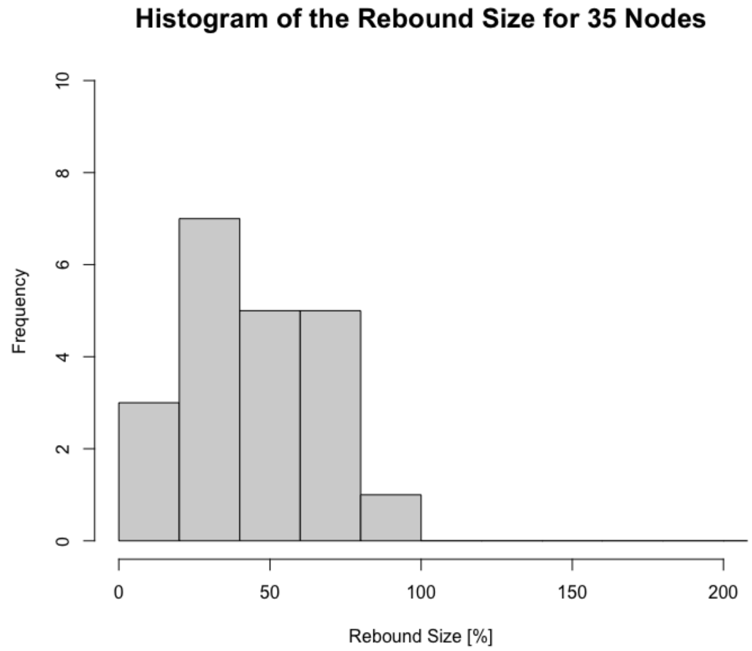



Figure 7.3: Distribution of the Rebound size for instances with 35 Nodes.

After analyzing these 3 graphs, several trends appeared. These can be explained by the trade-off the decision-maker faces between transportation and procurement costs. As a reminder, suppliers located far away from the depot are cheaper, but traveling to those points is more costly.

First, we note that with few nodes and so few suppliers available, the optimal vehicle tour rarely changes despite the efficiency improvement of the vehicle. For each generated instance, if a change in supplier selection happened, this occurred only once during the 10 iterations of the instance and every time, it was a BF that appeared. Indeed, with fewer suppliers, the distances between the nodes tend to be longer. The change in the decision will therefore have a big impact on the distance traveled. That is why BF are more likely to appear when changes in the optimal tour are observed.
In Figure 7.4 is drawn a change of vehicle tour for an instance with 7 nodes. We can see that the fuel efficiency improvement drastically increased the total traveled distance, which resulted in a BF of 630%.

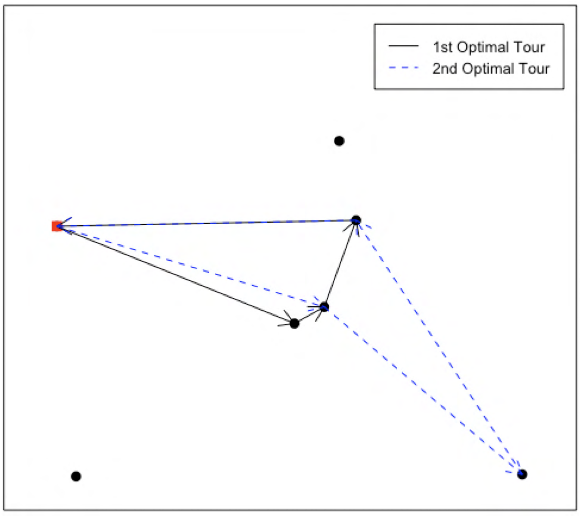



Figure 7.4: Optimal vehicle tours for an instance with 7 nodes. Occurrence of a BF of 629,2%. The depot is represented in red.

Then, when the number of nodes is larger, the distances between them tend to be relatively shorter. We noticed that changes in supplier selection after a fuel efficiency improvement occurred more often, but with a smaller impact on the length of the optimal tour. Indeed, one or two suppliers located further away and offering more advantageous prices replaced closer suppliers. It slightly increased the traveled distance and a partial RE occurred. This explains why this type of RE were more frequently observed with large numbers of nodes. Finally, it also justifies why the average Rebound size was lower in those conditions.
This explanation can be illustrated by Figure 7.5, where 2 partial RE appeared after two small changes in the optimal vehicle tour.

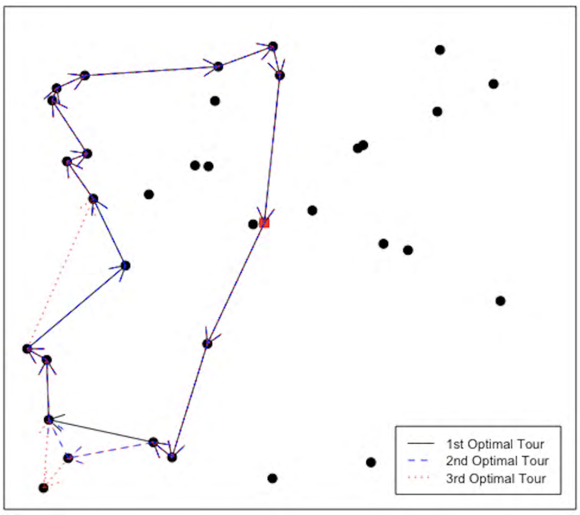



Figure 7.5: Optimal vehicle tour for an instance with 35 nodes. Occurrence of Partial RE of respectively 18,7% and 24,2%.
The depot is represented in red.

In conclusion the number of nodes has a notable influence on the occurrence and the type of RE that we observe in a TPP. Firstly, partial RE tends to occur more frequently when the number of nodes increases. Secondly, the average rebound size decreases with the number of nodes in the network and tremendous BF happens for instances with smaller number of nodes.

## 7.2 Products

In this section, we will vary the number of products to determine if it can influence the occurrence of RE and BF. For each instance generated, only one vehicle is used to purchase the product(s). The network is still composed of 10 nodes. Obviously, the same methodology has been used but this time by varying the number of products. The tests have been conducted for instances with 1, 3, 5, 7, 10, 15, 20, 25, and 30 products.

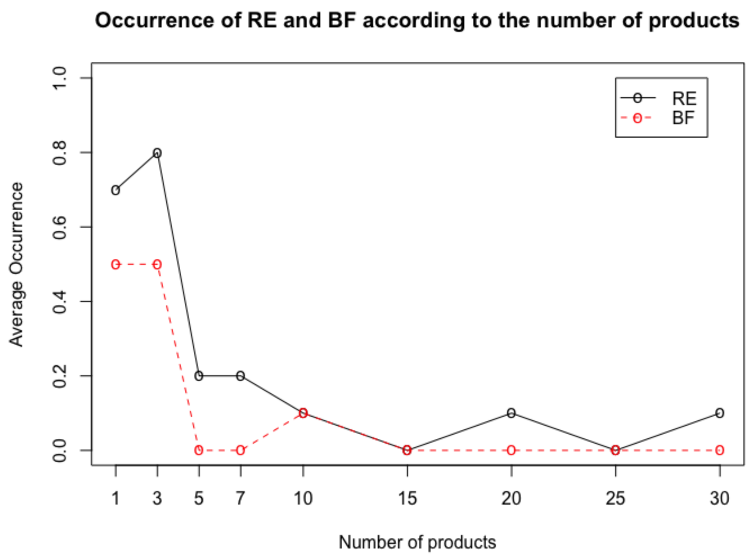



Figure 7.6: Average occurrence of RE and BF per instance according to the number of products.

To begin, in Figure 7.6, we notice that both the number of RE and the number of BF decreased when several products are purchased. Only one BF over 60 instances has been recorded when more than 3 products are procured. Also, the number of RE considerably decreased when more than 3 products are bought. Nevertheless, there is a logical explanation behind this trend. Indeed, when the number of products increases, the trade-off between procurement cost and traveling costs becomes strongly unbalanced.

Table 7.1 illustrates the evolution of the costs allocation according to the number of products. It was constructed using the data of transport and procurement cost among all instances of a given number of product. It is important to mention that for each instance, only the first iteration was considered, i.e with a fuel efficiency of 40 *l/100km*.

| Number of Products | 1 | 3 | 5 | 7 | 10 | 15 | 20 | 25 | 30 |
|---|---|---|---|---|---|---|---|---|---|
| Average Transport Cost [€] | 377,43 | 462,37 | 518,94 | 500,75 | 528,29 | 505,19 | 502,42 | 540,64 | 508,21 |
| *% of Total Cost* | *63%* | *39%* | *31%* | *26%* | *19%* | *12%* | *9%* | *8%* | *7%* |
| Average Procurement Cost [€] | 223,60 | 726,48 | 1171,22 | 1389,11 | 2322,02 | 3725,83 | 5160,81 | 5899,30 | 6932,41 |
| *% of Total Cost* | *37%* | *61%* | *69%* | *74%* | *81%* | *88%* | *91%* | *92%* | *93%* |

Table 7.1: Evolution of the cost repartition according to the number of products.

It is clear that the weight of procurement costs is getting larger as the number of products increases. This is due to the demand generated for each product. As soon as we decided to purchase a new product, its demand was added to the already-existing demand for other products. In other words, the total demand, as well as the procurement cost, expands when the number of products increases. That is why less RE or BF are observed. Indeed, with a lot of products, it becomes optimal to visit the suppliers located far away and offering the lowest prices no matter the distance to get there. For example, from Table 7.1, we notice that despite the transport cost being relatively stable, the procurement cost skyrockets with the number of products. This means that no matter the instance generated, when at least 5 products are bought, the decision-maker almost directly selects the most distant suppliers to minimize procurement costs.

To avoid the procurement cost excessively increasing with the number of products, a different approach can be experimented. In reality, a company could decide to buy various types of products without changing the total demand. That is why we decided to arbitrarily set the total demand to 300 units to determine if occurrences of RE would still follow the same trend. It means that if 3 products are purchased, the demand for each of them would be equal to 100 units.

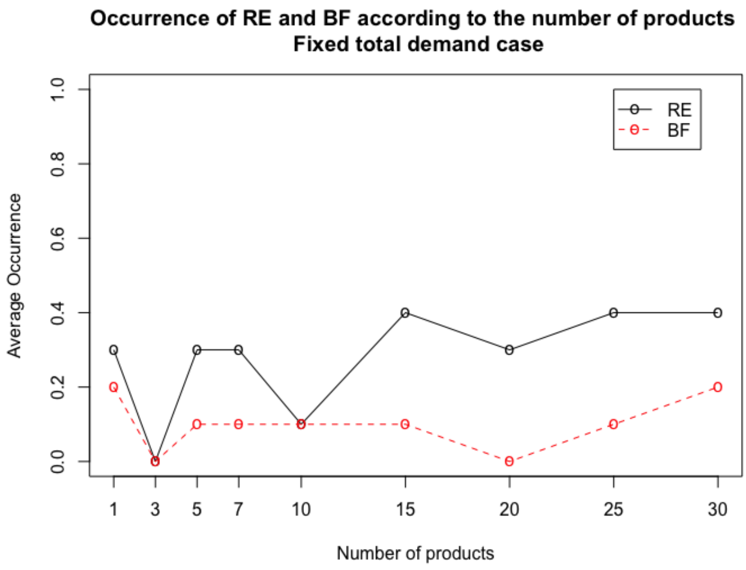



Figure 7.7: Average occurrence of RE and BF per instance according to the number of products for the fixed total demand case.

On the graph in Figure 7.7, we directly notice that the trend is not the same anymore. BF and RE are more likely to occur even with more products purchased. Furthermore, as we can see in Table 7.2 the proportion of the transport cost is not decreasing anymore with the number of products, as expected.

| Number of Products | 1 | 3 | 5 | 7 | 10 | 15 | 20 | 25 | 30 |
|---|---|---|---|---|---|---|---|---|---|
| Average Transport Cost [€] | 487,01 | 489,05 | 472,08 | 484,19 | 524,68 | 517,79 | 520,71 | 519,38 | 474,62 |
| *% of Total Cost* | *31%* | *28%* | *31%* | *31%* | *31%* | *34%* | *31%* | *34%* | *27%* |
| Average Procurement Cost [€] | 1100,21 | 1272,54 | 1053,39 | 1075,97 | 1181,42 | 1005,02 | 1173,27 | 1004,81 | 1311,65 |
| *% of Total Cost* | *69%* | *72%* | *69%* | *69%* | *69%* | *66%* | *69%* | *66%* | *73%* |

Table 7.2: Evolution of the cost repartition according to the number of products for the fixed total demand case.

In conclusion, the influence of the number of products on the occurrence of the RE depends on the company policy regarding its total demand. If the total demand is fixed no matter the number of products to procure, then a fuel efficiency improvement can induce the optimal tour to change. RE and BF could actually happen regardless of the number of products. On the other hand, if the total demand increases with the number of products, the procurement cost will skyrocket and represent a very large portion of the total cost. As a result, only the suppliers offering the best prices will be selected to minimize those procurement cost. Therefore, significantly less RE and BF will happen for instances with a larger number of products.

## 7.3 Vehicles

In this section, we will vary the number of vehicles used. The transportation network is still composed of 10 nodes and one single product has to be procured.

For this variant of the problem, we assumed that the vehicle capacity was equal to 20 units. Therefore, when a company owns multiple vehicles, it means that its demand in terms number of units to procure is considerably bigger than in the single vehicle case.

As a result, we increased the demand each time a new vehicle was added to the problem. In Table 7.3, we denoted the random distributions used to generate the demand according to the number of vehicles.

| Number of vehicles | Demand distribution |
|---|---|
| 1 | $\mathcal{U}(5, 20)$ |
| 2 | $\mathcal{U}(20, 40)$ |
| 3 | $\mathcal{U}(40, 60)$ |
| 4 | $\mathcal{U}(60, 80)$ |

Table 7.3: Random distribution according to the number of vehicles.

The choice not to exceed 80 units for 4 vehicles is linked to the computational power needed to solve the 100 iterations. With a demand request exceeding this number, the time needed to solve those 100 iterations with 4 vehicles was too demanding.

In Figure 7.8, we can observe the influence of the number of vehicles on the occurrence of RE and BF. We notice that RE tended to happen more often when more vehicles are used by the company. Regarding BF, their number has increased linearly with the number of vehicles.

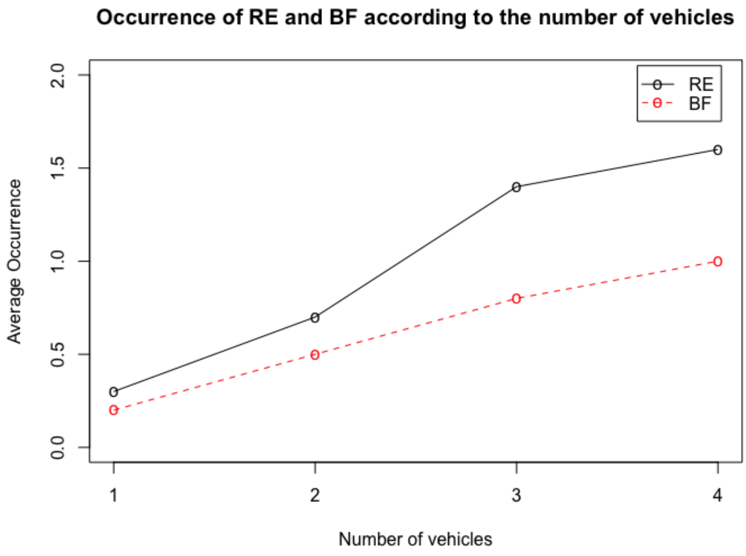
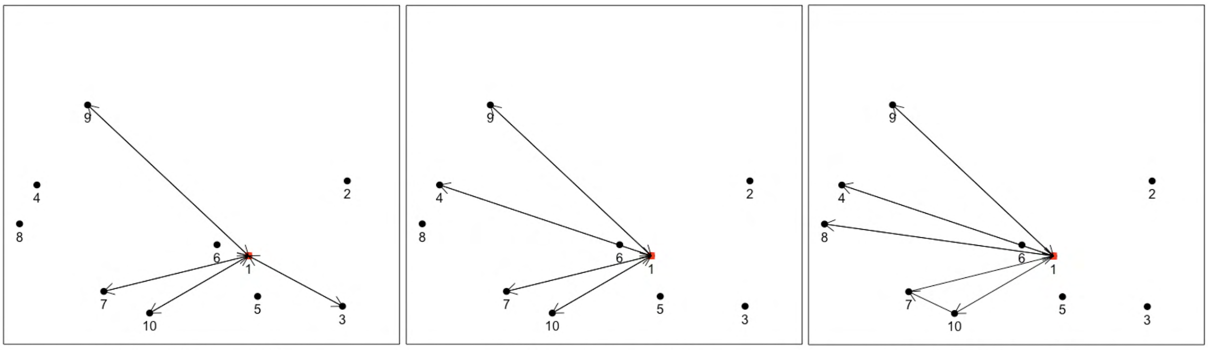



Figure 7.8: Average occurrence of RE and BF per instance according to the number of vehicles.



(a) 1st Optimal Tour (b) 2nd Optimal Tour (c) 3rd Optimal Tour

Figure 7.9: Comparison of the optimal tours for an instance with 4 vehicles.

To better understand why we observed more RE and BF, we depicted the optimal vehicle tours of an instance with 4 vehicles (Figure 7.9). Actually, two BF occurred for this instance: one of 168,9% and another one of 118,5%. As we can see, the number of visited suppliers per vehicle is much lower than in the one-vehicle case. It means that each vehicle tour will be more flexible and therefore more likely to change after an efficiency improvement.

For example, the vehicle visiting supplier 3 in situation (a) will now visit supplier 4 in (b). Its tour completely changed in order to visit another supplier offering a lower price. Indeed, it would not be optimal to visit both supplier 4 and supplier 3 using the same vehicle. Its tour is now oriented in a totally different direction. The same situation happened between situations (b) and (c). A vehicle changed totally its tour to visit supplier 8 instead of supplier 7. On the other hand, another type of change in terms of vehicle tours can be observed. Sometimes a vehicle may change its tour after an efficiency improvement, by visiting an additional supplier relatively close to its initial tour. That is what happened in situation (c). The vehicle visiting supplier 10 in (b) added supplier 7 to its initial tour. In other words, small vehicle tour changes can also happen.

In conclusion, when multiple vehicles are available, the number of viable options increases, resulting in more potential occurrences of RE and BF.

### 7.3.1 Traveled Distance Policy

In the transport sector, policies aiming at consumers multiplied over the last decade. Their purpose is to encourage them to purchase energy-efficient cars or to influence consumers' car usage (Steren et al., 2022). Recent studies found that a distance-traveled tax is an efficient policy tool. It may offset the incentive to increase the usage of vehicles when more efficient cars are bought by consumers. In fact, several states in the USA are considering a distance-traveled tax. Such a tax could be adjusted depending on car attributes such as the car's level of GHG emissions (Steren et al., 2022).

After concluding that RE and BF occurrence tended to increase with the number of vehicles, we decided to implement this specific distance-traveled policy. The latter aims at penalizing a company when its total traveled distance exceeds a given threshold. The goal is to understand if this kind of policy can mitigate the RE in our problem.

To do so, we modified the model described in Chapter 4. Firstly, a term was added to the objective function (equation 7.1). It now includes the transport cost, the procurement cost, and a penalty cost if the total traveled distance exceeds the threshold. A cost of 2€ per extra *km* has been arbitrarily chosen. The non-negative variable $a$ represents the number of kilometers traveled by the fleet of vehicles exceeding the threshold parameter $T$.

$$\min C = \sum_{k \in K} \sum_{v \in F} \sum_{i \in M} c_{ik}\, z_{ik}^{v} + \sum_{v \in F} \sum_{(i,j) \in A} d_{ij}\, x_{ij}^{v}\, \frac{f}{100} + 2\, a \tag{7.1}$$

As showed by constraint 7.2, with this new policy, it is indeed the distance traveled by the entire fleet that is taken into account, and not the distance traveled by each vehicle individually.

$$\sum_{(i,j)\in A} \sum_{v\in F} x_{i,j}^{v}\, d_{i,j} \le T + a \tag{7.2}$$

In addition, the distance threshold $T$ depends on the number of trucks the firm owns. We tested 3 different allowances per vehicle : 400, 500, and 700 $km$. It means that for instance, if the company has 3 vehicles and the allowance is fixed at 500 $km$ per vehicle, the threshold $T$ is equal to 1500 $km$. Therefore, every extra km over 1500 $km$ will be charged 2€.

In Figures 7.10 and 7.11 is depicted the average occurrence of RE and BF according to the number of vehicles and for each given vehicle allowance. Of course, these must be put in parallel with Figure 7.8. We directly noticed the influence of this new policy.

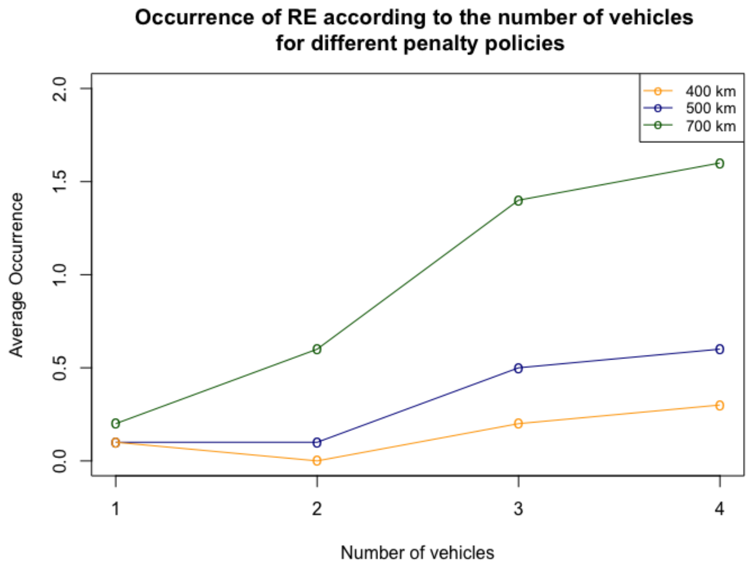



Figure 7.10: Average occurrence of BF per instance according to the number of vehicles. Impact of different policies.

Both RE and BF occurrence tended to decrease when an allowance of 400$km$ or 500$km$ per vehicle was set. Indeed, we note a huge decrease in RE for 3 and 4 vehicles with the orange and the blue curve. Besides, from Table 7.5, we see that the penalty cost only represents 16% and 9% of total cost respectively, when an allowance of 500$km$ was set.

Thus, the increase in total cost was relatively small after the policy change.

Nevertheless, smaller allowance implies tremendous penalty cost for companies operating with 1 or 2 vehicles, as depicted in Tables 7.4 and 7.5. Even tough a slight decrease in the average occurrence of RE and BF was observed compared to the initial situation in Figure 7.8, it came with a considerable increase in cost for smaller firms. As a result, one can argue that this kind of policy is not effective for companies owning 1 or 2 vehicles.

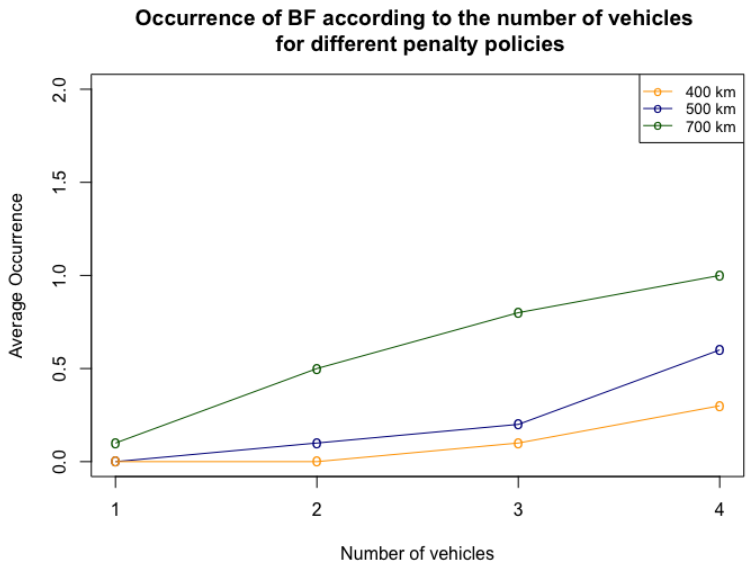



Figure 7.11: Average occurrence of BF per instance according to the number of vehicles. Impact of different policies.

| Number of vehicles | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Average Penalty Cost [€] | 737,09 | 429,29 | 415,41 | 378,38 |
| *% of Total Cost* | *65%* | *41%* | *31%* | *25%* |

Table 7.4: Importance of the penalty cost according to the number of vehicles. 400$km$ allowed per vehicle

| Number of vehicles | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Average Penalty Cost [€] | 558,95 | 208,66 | 164,92 | 113,95 |
| *% of Total Cost* | *59%* | *26%* | *16%* | *9%* |

Table 7.5: Importance of the penalty cost according to the number of vehicles. 500$km$ allowed per vehicle

Concerning the 700 $km$ allowance, the curve is very similar to the black one in Figure 7.8. It simply means that this allowance is ineffective to address occurrences of RE and BF.

This is also confirmed by Table 7.6 where the average penalty cost for the instances with 3 and 4 vehicles was equal to 0€. In other words, the threshold parameter in constraint 7.2 is too high .

| Number of vehicles | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Average Penalty Cost [€] | 260,08 | 7,79 | 0,00 | 0,00 |
| *% of Total Cost* | *40%* | *1%* | *0%* | *0%* |

Table 7.6: Importance of the penalty cost according to the number of vehicles. $700km$ allowed per vehicle

In conclusion, introducing a new policy to mitigate the RE can be beneficial if we apply it to companies with more than 2 vehicles. Indeed, this policy implies a large increase of the costs for the instances with 1 and 2 vehicles. Above all, only a very small decline in terms of RE and BF happened. To cut a long story short, implementing this policy for firms with 1 or 2 vehicles seems very costly for companies and not efficient.

## 7.4 Exclusivity of Products

The aim of this section was to analyze the effect of exclusive product availability on the occurrence of RE and BF. A product considered as exclusive was made available at only one specific supplier. As a result, to meet the demand for these products, the company must necessarily travel to a specific node.

In order to observe the influence of exclusive product availability, 4 scenarios will be evaluated:

Scenario 1: The company has to procure 3 products. These products are available in restricted quantity at every supplier. In other words, the company do not have to procure any exclusive product.

Scenario 2: Among the 3 products that the company has to procure, one of them is exclusively available at a selected supplier. The latter only offers the exclusive product. On the other hand, regular products are still available at the 8 other suppliers in restricted quantity.

Scenario 3: Among the 3 products that the company has to procure, two of them are exclusively available at selected suppliers. Therefore, one supplier is offering the first exclusive product and another supplier is offering the second one. On the other hand, the regular product is still available at the 7 other suppliers in restricted quantity.

Scenario 4: Among the 3 products that the company has to procure, all of them are exclusively available at selected suppliers. Therefore, 3 suppliers are exclusively offering one of the 3 products.

For each of those scenarios, we applied our methodology to compare the average occurrence of RE and BF. We generated instances with 10 nodes, 3 products and 1 vehicle. The demand for each product is generated according to a uniform distribution[1], as described in Chapter 5. In addition, suppliers offering regular products have a randomly generated capacity[2]. Finally, we assume that suppliers offering an exclusive product have enough capacity to meet the demand of the company.

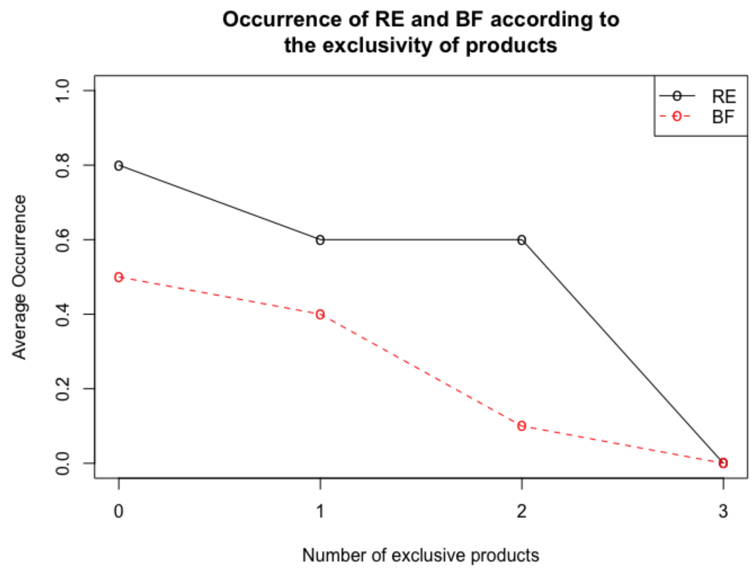



Figure 7.12: Average occurrence of RE and BF per instance according to the number of exclusive products.

Figure 7.12 depicts the average occurrence of RE and BF according to the number of exclusive products that the firm had to procure. We see that having to purchase products that are exclusively available at specific suppliers had a clear impact on the RE and BF. In the first scenario, the company had to buy 3 regular products. To do so, a subset of suppliers had to be visited. Therefore, the quantity purchased at each of the node depends

[1] $d_k = \mathcal{U}(20, 100) \;\; \forall k \in K$

[2] $K_{ik} \sim \mathcal{N}(\frac{2d_k}{n}, \frac{2d_k}{4n})$ where $d_k$ is the demand for product $k$ and $n$ the number of suppliers offering this product. Not that the formula only applies to regular products.

on the trade-off between procurement cost and traveling cost. This is the scenario we have been describing before. As a reminder, with an improvement in energy efficiency, it might be optimal to travel further and buy products from cheaper suppliers. As a result, RE and BF can occur relatively often. For instance, in Figure 7.13, we can see that after an efficiency improvement, it becomes optimal to visit the supplier 3 which offers the second cheapest prices. This change in the vehicle tour created a BF of 154%.

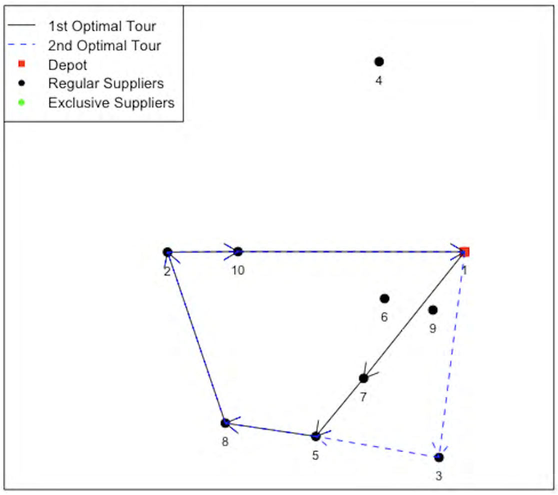



Figure 7.13: Optimal vehicle tour for an instance of scenario 1.
Occurrence of BF of 154%.

Scenarios 2 and 3 are intermediate cases in which the company has to procure a mix between regular products and exclusive products. We noticed that BF tended to occur less often compared to scenario 1 in which all products were available anywhere.

Besides, in scenario 3, the company had to procure the two exclusive products from specific suppliers. On the other hand, the remaining regular product will be purchased at other suppliers taking into consideration two factors: the trade-off between procurement and traveling cost, and the location of the two exclusive suppliers that had to be visited. As a result, when RE occurred, the size tended to decrease because the optimal tour is less flexible than before. This is illustrated in Figure 7.14. The vehicle tour now includes supplier 6 because he is the only one offering Product 2. After an efficiency improvement, a partial RE of 80% occurred because it was cheaper to go to supplier 2 offering the most attractive prices for the regular product. It is not optimal anymore to go to node 3, the RE was limited by the fact that the company had to visit suppliers 5 and 6. By visiting specific suppliers to get exclusive products, we have fewer viable options.

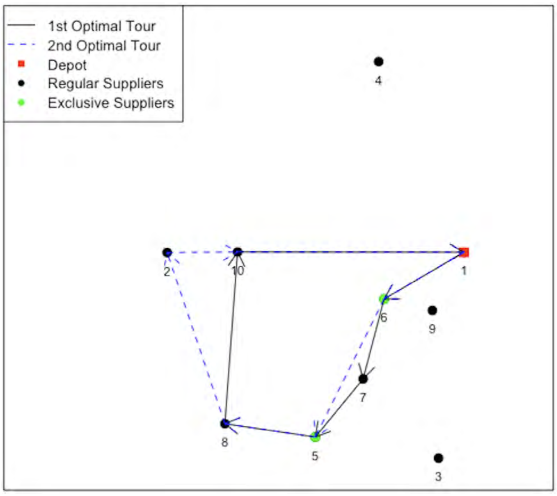



Figure 7.14: Optimal vehicle tour for an instance of scenario 3.
Occurrence of partial RE of 80%.

Scenario 4 is an extreme case in which the company has to procure 3 exclusive products. Therefore, the 3 specific suppliers offering these products will be visited. Obviously, the optimal tour will never change despite any improvement in energy efficiency. This is the reason why no RE and BF occurred in this case. Figure 7.15 illustrates this situation. There is only one option to meet the demand. We must visit the same three suppliers no matter the efficiency of the vehicle.

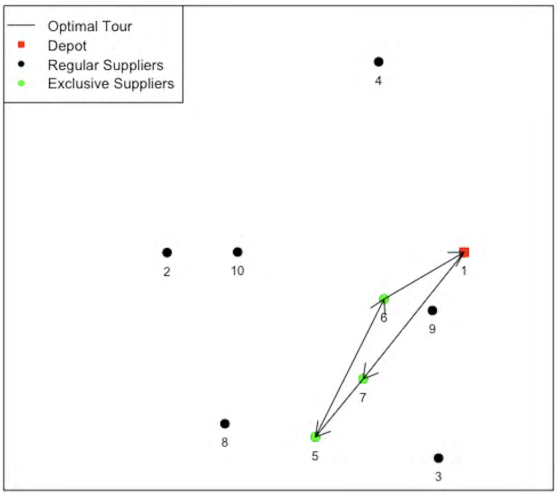



Figure 7.15: Optimal vehicle tour for an instance of scenario 4.
No RE or BF occurred.

In addition, we can observe the evolution of the cost according to the number of exclusive products. As we can observe in Figure 7.16, the procurement cost tends to increase with the number of exclusive products. This is explained by the fact that fewer options are viable now. We have no other choice than to visit the exclusive suppliers, even if they are located closer to the depot and thus, offer a high price. We can observe that in Figure 7.15. The suppliers offering the exclusive products are quite close to the depot. That is why the procurement cost exploded while the transport cost slightly decreased compared to scenario 3.

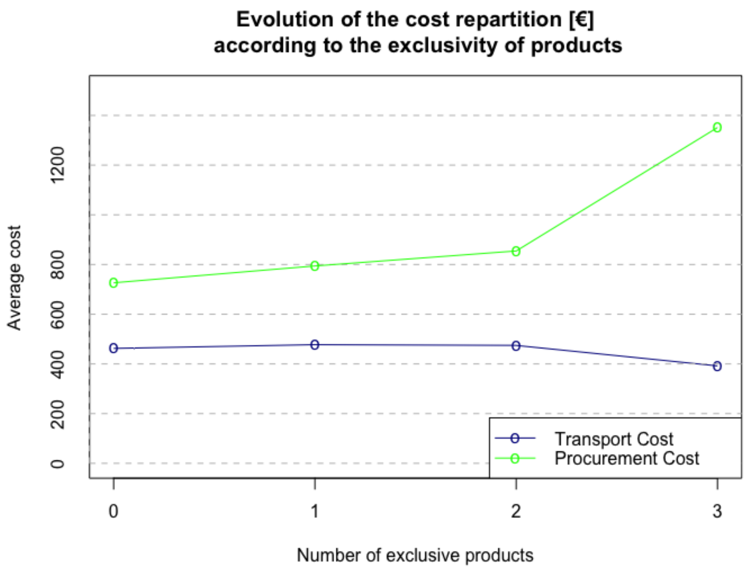



Figure 7.16: Evolution of the cost repartition according to the number of exclusive products.

In conclusion, if a firm decides to procure products that are available only at specific suppliers, the number of BF will tend to decrease. Indeed, the optimal tour is less flexible than before because the suppliers offering those specific products must be visited. Besides, in the extreme scenario where all the products are exclusive, BF and partial RE cannot occur anymore. This is because the vehicle tour will not change no matter the improvement in fuel efficiency.

## 7.5 Quantitative Summary

Previously, we analyzed the influence of different characteristics, parameters, and variants of the TPP on the occurrence of RE and BF. This section aims to summarize what variables influence the RE. To do so, we chose to use two statistical methods: logistic regression and decision tree. It is important to note that our goal here was to quantitatively understand what drives the occurrence of RE and evaluate if this confirmed the trends we described in the previous section. Therefore, we did not seek to fit a statistical model that can predict the occurrence of RE, but rather use these models as a descriptive tool.

In the coming sub-sections, we first present how we constructed the dataset that was used for the analysis. Then, we will briefly explain what a logistic regression is before interpreting the output. Finally, we will do the same for the decision tree model.

### 7.5.1 Dataset Construction

To perform the analysis, a dataset was constructed based on the instances that were generated for the previous experiments. Therefore, each observation of the dataset represents a generated instance, and the different characteristics and specificities of each instance are summarized by the following variables:

- *Product*: Numerical variable indicating the number of products that the company had to procure.
- *Vehicle*: Numerical variable indicating the number of vehicles composing the fleet of the company.
- *Node*: Numerical variable indicating the number of nodes composing the transportation network.
- *TotalExpDem*: Numerical variable indicating the total expected demand that the company had to meet. [units]
- *Exclusivity*: Binary variable indicating whether or not the company had to procure products that were exclusively available at select suppliers.

- *NumExcl*: Numerical variable indicating the number of exclusive products that the company had to procure.
- *TravDistPolicy*: Binary variable indicating whether or not the company faced a distance-traveled policy.
- *DistAllowance*: Numerical variable indicating the allowance per vehicle set by the distance-traveled policy that the company faced[3]. [km/vehicle]
- *RE*: Numerical variable indicating the number of RE that occurred among the 10 iterations of this instance.
- *dummy.RE*: Binary variable indicating whether or not a RE occurred among the 10 iterations of this instance.

In total, 510 instances were generated for the experiments. Therefore, the dataset will be composed of 510 observations and 10 variables. Table 7.7 illustrates the structure of the dataset with a random sample of the observations.

| Instance | Product | Vehicle | Node | TotalExpDem | Exclusivity | TravDistPolicy | DistAllowance | NumExcl | RE | dummy.RE |
|---|---|---|---|---|---|---|---|---|---|---|
| 450 | 1 | 2 | 10 | 30 | No | Yes | 700 | 0 | 1 | TRUE |
| 388 | 1 | 4 | 10 | 70 | No | Yes | 500 | 0 | 0 | FALSE |
| 337 | 1 | 3 | 10 | 50 | No | Yes | 400 | 0 | 0 | FALSE |
| 213 | 7 | 1 | 10 | 300 | No | No | 1,00E+05 | 0 | 1 | TRUE |
| 351 | 1 | 1 | 10 | 12.5 | No | Yes | 500 | 0 | 0 | FALSE |
| 463 | 1 | 4 | 10 | 70 | No | Yes | 700 | 0 | 2 | TRUE |
| 277 | 1 | 1 | 10 | 12.5 | No | No | 1,00E+05 | 0 | 0 | FALSE |
| 148 | 15 | 1 | 10 | 900 | No | No | 1,00E+05 | 0 | 0 | FALSE |
| 11 | 1 | 1 | 5 | 60 | No | No | 1,00E+05 | 0 | 0 | FALSE |
| 165 | 25 | 1 | 10 | 1500 | No | No | 1,00E+05 | 0 | 0 | FALSE |
| 60 | 1 | 1 | 20 | 60 | No | No | 1,00E+05 | 0 | 1 | TRUE |
| 435 | 1 | 1 | 10 | 12.5 | No | Yes | 700 | 0 | 0 | FALSE |
| 439 | 1 | 1 | 10 | 12.5 | No | Yes | 700 | 0 | 1 | TRUE |
| 442 | 1 | 2 | 10 | 30 | No | Yes | 700 | 0 | 2 | TRUE |
| 282 | 1 | 2 | 10 | 30 | No | No | 1,00E+05 | 0 | 1 | TRUE |
| 505 | 3 | 1 | 10 | 180 | Yes | No | 1,00E+05 | 3 | 0 | FALSE |
| 10 | 1 | 1 | 3 | 60 | No | No | 1,00E+05 | 0 | 0 | FALSE |
| 484 | 3 | 1 | 10 | 180 | Yes | No | 1,00E+05 | 1 | 1 | TRUE |
| 209 | 5 | 1 | 10 | 300 | No | No | 1,00E+05 | 0 | 0 | FALSE |
| 42 | 1 | 1 | 15 | 60 | No | No | 1,00E+05 | 0 | 2 | TRUE |

Table 7.7: Sample of 20 instances from the dataset.

It is important to explain why we decided to take the total expected demand of each instance into account. Indeed, in Section 7.2, we found out that the average occurrence

[3]If the company was not facing any distance-traveled policy, then the *DistAllowance* variable was set to 1,00E+05, which represented a unlimited allowance.

of RE and BF was decreasing with the number of products that the company had to procure. Nevertheless, this was due to the increase in procurement cost induced by the way the total demand was generated. As a reminder, the latter was increasing with the number of products. Besides of that, as the total demand was growing, the cost trade-off was shifting towards procurement cost and the occurrence of RE was decreasing.
As a result, we found important to include the total expected demand in the dataset in order to capture the effect of this parameter on the occurrence of RE. Otherwise, the output would have been biased because potential results implied by the total expected demand could be attributed to other variables.

Finally, to have a broader look at the dataset, Figure 7.17 depicts the frequency of the number of RE that occurred per instance. We notice that for more than 300 generated instances, no RE occurred.

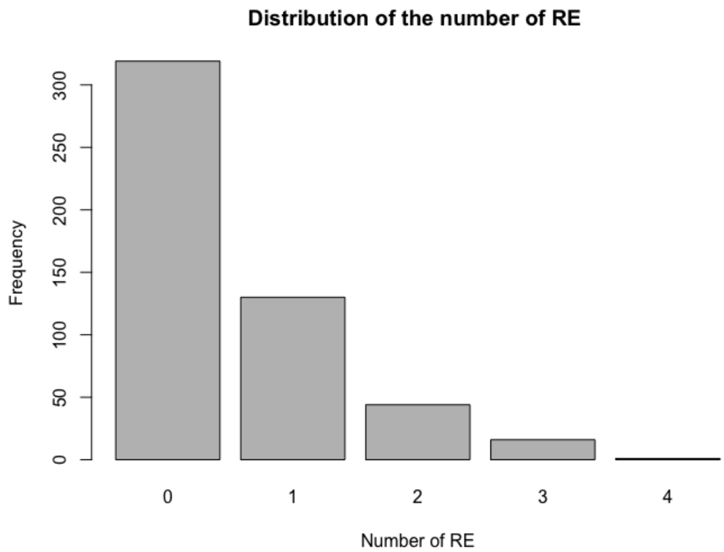



Figure 7.17: Distribution of the number of RE in the data.

### 7.5.2 Logistic Regression

The first statistical method that we used was logistic regression. It directly estimates the *a posteriori* probabilities, i.e the probability that an observation belongs to a class given certain attributes. It can handle both categorical and numerical features which is an advantage. (Saerens, 2021)

In our case, the response variable was *dummy.RE*. Therefore, the model estimated the probability that a RE occurred or not, ie. that an observation belonged to class TRUE or FALSE. To do so, a model with all the variables except obviously *RE* was fitted in RStudio using the function *glm*.

```
Coefficients:
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)      -1.040e+03  2.071e+02  -5.021 5.13e-07 ***
Product           2.970e-02  1.943e-02   1.528 0.126427
Vehicle           1.271e+00  1.843e-01   6.893 5.47e-12 ***
TotalExpDem      -2.461e-03  7.190e-04  -3.422 0.000621 ***
Node              1.139e-01  2.409e-02   4.726 2.29e-06 ***
ExclusivityYes    2.568e+00  1.111e+00   2.311 0.020806 *
TravDistPolicyYes 1.029e+03  2.058e+02   5.003 5.65e-07 ***
DistAllowance     1.037e-02  2.070e-03   5.010 5.46e-07 ***
NumExcl          -1.292e+00  5.857e-01  -2.205 0.027419 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 7.18: Output of the logistic regression model.

Figure 7.17 summarizes the output of the fitted logistic regression. First, we can see that all p-values are below 5%, except the one of the variable *Product*. This means that there is a statistically significant association between the occurrence of RE and all variables except *Product*.

This strengthens the results obtained in Section 7.2. Indeed, increasing the number of products without changing the total expected demand does not have a big impact on the occurrence of RE. On the other hand, we notice that the association between the total expected demand and the occurrence of RE is confirmed by the very low p-value of this variable. Regarding the interpretation of coefficients $\beta_i$, $e^{\beta_i}$ represents the change in relative probability when the variable $i$ increases by one unit.

For example, when the number of nodes increased by one unit, the probability of RE occurrence increased by $1 - e^{0,1139} = 1 - 1,12 = 12\%$. On the other hand, when the number of exclusive products that the company has to procure increase by one unit, the probability of RE occurrence decreased by $1 - e^{-1,292} = 1 - 0,274 = -72,6\%$.

In addition, by looking at other coefficients, we note that *TotalExpDem* and *NumExcl* have a negative sign. This means that an increase in total expected demand or an increase in the number of exclusive products that the company has to procure lowers the probability to observe a RE.

### 7.5.3 Classification Tree

We will now fit a Decision Tree (DT) to visualize the variables that help to determine whether or not a RE occurred. A DT is a classifier taking the form of a hierarchical tree structure. It is a supervised machine learning algorithm that separates the data according to a set of rules. The advantage of this model is that the output is easy to understand and to interpret. Besides, it also produces feature selection which means that the DT selects the most relevant features predicting the dependent variable.
(Dougherty, 2012; Izenman, 2008) Every classification tree is composed of nodes and branches. At each decision node, the value of a feature is tested. The branches leaving that node correspond to the possible outcomes of that feature. The left branch of the tree represents the path to follow if the condition regarding the tested feature is met.

Again, a model with all the variable except *RE* was fitted in RStudio, but this time using the function *tree*.

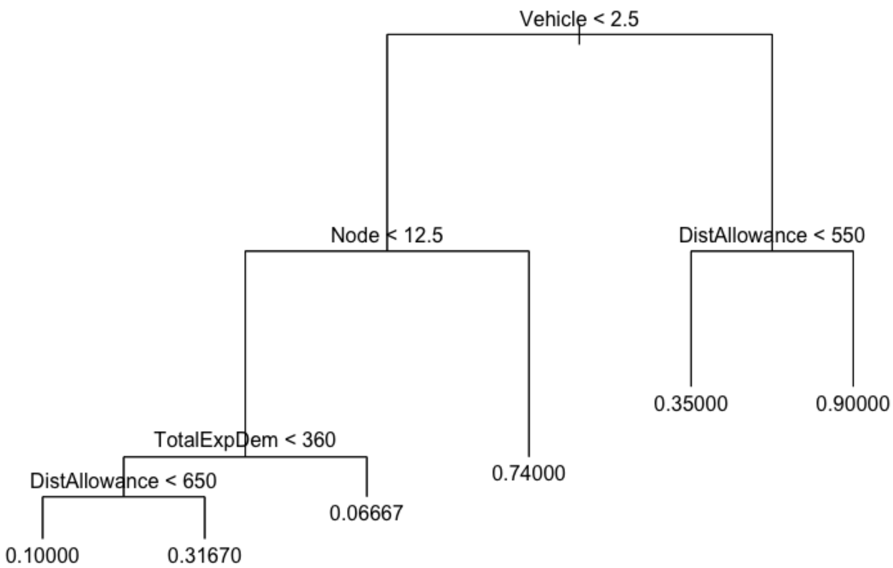



Figure 7.19: Output of the DT model.

Looking at Figure 7.19, we observe that the variables *Vehicle*, *Node*, *DistAllowance*, and *TotalExpDem* were selected in order to classify observations. The root node separates the instances with 1 or 2 vehicles from the one with 3 or 4 vehicles. If we look at the right

side of the tree, instances with more than 3 vehicles and a distance allowance greater than 500 *km/vehicle* have a high probability of RE occurrence.
On the other hand, instances with two vehicles or less, less than 12 nodes, and a total expected demand greater than 360 units have a very low probability of seeing a RE occur.

To conclude, from this DT, it seems that the variables having the biggest influence on the occurrence of RE were the number of vehicles, the distance allowance per vehicle, and the number of nodes composing the network.

# Chapter 8

# Discussion

First of all, it is important to quickly remind the context of our thesis as well as the research question we aim to answer.

As we know, the $CO_2$ emitted into the atmosphere by human activities is the main driver of global warming, and the transport sector represents a significant proportion of these emissions. Thus, over the past few years, governments have been implementing energy-efficient policies in order to consume less energy and emit fewer GHG. However, as explained before, the expected reduction in GHG emissions can be partially or sometimes totally offset due to RE. Evaluating what can lead to the occurrence of RE in this $CO_2$-emitting sector seems therefore essential. That is why we decided to answer the following research question: *"What drives the RE in transportation?"*.

Before addressing a deeper interpretation of the results, it is fundamental to highlight some parallels between our analysis and some key concepts presented in Chapter 3.

As a reminder, the RE is related to individual energy services and the energy needed to deliver that service. In fact, energy is consumed to produce what we call the "useful work", i.e. what is actually obtained from the use of energy. In our TPP model, it is represented by the kilometers traveled. The chemical energy of gasoline is transformed into mechanical energy and allows the car to travel a given distance. As a result, a given quantity of energy is consumed to enable the vehicle to travel from one place to another.

Then, we can use the typology established by Greening et al. (2000) to specify what types of RE would be observable in a simple application such as a TPP.

The type of RE we focused on is a direct RE called "Income effect". Indeed, by using a more efficient car, the cost of fuel consumption decreases. The company could therefore travel a greater distance than before but for an identical traveling cost. Of course, by increasing the distance traveled, a part of the expected energy savings would be offset, or worse more GHG could be emitted. In other words, a direct RE could occur.

In addition, the indirect RE, especially the "re-spending effect", also be observable in a similar situation in which a company wants to minimize its procurement cost.
For instance, in the long run, the money saved from the reduction in transport cost due to the energy efficiency improvement could be re-invested to buy other energy-intensive equipment. It could be, for example, another vehicle or machine that would allow the company to meet a larger demand. As a result, the demand for energy could finally increase and more GHG could be emitted.

After mentioning the type of RE that could be observed within the business application we modeled, it is key to explain why we decided to focus only on the income effect.
As mentioned, estimating indirect effects is a real challenge given the number of confounding variables. Taking into account indirect RE would mean that we should quantify all indirect use of energy from the company throughout the economy after an efficiency improvement. This means that our model should take into account all the other activities of the firm. We could then determine if the money saved after an efficiency improvement, is reinvested in another energy-intensive activity or not. This would allow us to observe both direct and indirect RE in a TPP application.
Nevertheless, this would have required too many assumptions. As a matter of fact, within a TPP the indirect RE is not really observable given the desired simplicity of the model and the absence of interaction with other energy services.

Concerning real-life application, when an income effect occurs, an individual decides to consume more energy in order to achieve a higher level of utility. In our model, this was translated by the objective function including traveling cost and procurement cost. It means that utility increases with a decrease in total cost. Then, we used a specific formula to generate the unit purchasing cost and create a balance between procurement cost and traveling cost that allows for occurrence of RE. As a reminder, the idea was that suppliers located far away from the depot should offer a lower price. However, in real life, other criteria than the price could balance the traveling cost. For instance, the different attributes of a product (quality, design, after-sale service, brand, durability, ...) could influence the utility that the decision-maker derives from it. It means that after an efficiency improvement, a product of better quality but with a higher price could influence the consumer to travel further because it would increase his overall utility.

Now that we highlighted the parallels between the key concepts of the literature and our application, we can now focus on the interpretation of the results obtained in Chapter 7.

Firstly, we decided to vary the number of suppliers included in the transportation network to find out to what extent it could impact the occurrence of RE. For each of the generated instance, a map of 500 *km* by 500 *km* was used.
In real life, it represents the area in which potential suppliers and the depot are dispersed. If fewer suppliers are present in this area, the distances between them will usually be longer. It would therefore require a big efficiency improvement compared to the initial situation before observing a change in the optimal tour. Besides, if a change happens, it means that the total traveled distance would drastically increase and a BF could occur. On the other hand, if a lot of suppliers are located in the area of the firm, the distances between each of them will tend to be shorter. Thus, changes in decision-making will be likely to occur more often. Indeed, small efficiency improvements would enable driving further to visit another supplier and achieve a higher level of utility.

Secondly, we wanted to evaluate if the number of products had an impact on the occurrence of RE. We found out that the occurrence of RE and BF was decreasing with the number of products that the company had to procure. Nevertheless, this was due to the increase in total demand that shifted the cost trade-off in a considerable way towards the procurement cost.
Therefore, it was not really the number of products that had an influence on the occurrence of RE but rather the procurement cost in a broader way. As a side note, the increase in procurement cost can be due to either a higher unit purchasing cost or an increase in the number of units to procure. In our case, the prices of the products were always generated in the same way and only the demand varied. Nevertheless, what actually influences the occurrence of RE is the amount of money that the company will spend to procure the needed products.

This intuition was confirmed in Section 7.5. Indeed, with the introduction of the variable representing the total expected demand of each instance, the association between *Product* and the occurrence of RE was not even statistically significant.
Then, we assessed different scenarios of product exclusiveness. We clearly noticed that having to purchase products that are exclusively available at specific suppliers had a clear impact. The number of BF decreased because the company had to visit pre-defined nodes and this lowered the flexibility of the optimal tour.
We can easily think about real-life situations in which this conclusion can be valid. For example, a restaurant owner can choose among several supermarkets for the basic ingredients that he needs for his dish. However, for premium ingredients, he must visit a delicatessen. The more premium products his dish contains, the less flexible he will be in terms of places he can visit. As result, it will be less likely that RE or BF occurs.

Thirdly, the influence of the number of vehicles was investigated. As a reminder, for a majority of our tests, we assumed that the vehicle capacity was sufficient to transport the total demand. However, in real-life cases, it seems logical to suggest that as a company grows in size, its demand and number of vehicles will increase as well. That is why we decided to experiment with the influence of the number of vehicles on the occurrence of RE. Actually, we observed an increase in the occurrence of RE and BF with the number of vehicles.
After that, we wanted to test whether implementing a distance-traveled tax would reduce the number of RE and BF. Those types of policies aiming at influencing consumers' car usage, multiplied over the last decade. After putting in place such a policy, we noticed that the number of RE and BF drastically decreased for bigger companies with several vehicles. Therefore, the role of policymakers would be to reduce the number of rebound effects while introducing a tax that would remain viable for companies.

As a side note, we also tested other variants of the TPP. We modeled an Asymmetric Traveling Purchaser Problem (ATPP). However, the implementation of this feature did not seem to have any influence on the occurrence of the RE. There was no significant difference in the results compared to the model with symmetric distances.
On the other hand, we also tested a variant with unrestricted supplier capacity. Only the supplier maximizing the trade-off between transport cost and procurement cost was visited. After an efficiency improvement, a RE could occur when it became optimal to travel

further and buy all the required products from another supplier offering better prices. In this case, the occurrence of RE and BF was indeed influenced, but the conclusions were not very valuable.

To conclude this chapter, it is important to point out to what extent our results relate or differ from previous research. In Chapter 3, we presented the study from Jaehn and Meissner (2022) that discussed the RE within a TPP. First, the authors chose a specific node configuration representing 40 cities from the Ruhr area in western Germany. On the other hand, we decided to randomly generate the coordinates of the nodes so that our results are not biased by any specific node configuration. In that sense, our analysis can be more general. In comparison, we also evaluated the impact of the number of vehicles and nodes on the occurrence of RE while Jaehn and Meissner stuck to a configuration with 40 nodes and 1 vehicle for all their generated instances. Finally, on our side, the exclusivity of products and the implementation of a distance-traveled tax were discussed.

# Chapter 9

# Conclusion

As a reminder, this thesis aimed to identify what drives the occurrence of RE in transportation. To do so, we modeled a TPP to represent a real-life business application in which a company has to minimize its procurement and transport cost while meeting demand. We used the optimization software AIMMS with CPLEX 20.1 to generate and solve 510 instances of the problem with varying characteristics.

From our results, it can be concluded that four variables can influence the occurrence of RE in a transportation network. On the one hand, RE tended to increase with the number of potential suppliers from which the firm can choose and the number of vehicles that the company owns to procure the products. On the other hand, the exclusivity of the products, as well as the introduction of a distance-traveled policy, reduced the occurrence of RE.

Nonetheless, the findings of this thesis have to be seen in the light of some limitations. First, the goal of our thesis was to evaluate the impact of given characteristics and parameters on the occurrence of RE. To be able to experiment as many variants of the problem as possible while having enough data to draw valid conclusions, we decided to generate and solve 10 instances of each given problem. This number was set considering the computational power and time limitations. For example, while analyzing the impact of the number of vehicles, we faced limitations due to computations limits. Therefore, in this case, generating and solving more than 10 instances was not possible.

In addition, while computing the RE, we assumed that the fuel consumption was only determined by the distance driven. In reality, other factors such as the type of route,

driving style, or the vehicle load could influence the effective fuel efficiency of the vehicle, and therefore the size of the rebound.
Then, when we discussed the implementation of a distance-traveled policy, we focused on the potential effect it could have on the direct RE. In reality, policymakers need to take into account a wide range of confounding variables to avoid undesirable outcomes to arise after setting this kind of tax. As a result, the generalization of the results regarding this policy are limited by the simplicity of the model.

To better understand the implication of our results, future studies could focus on four main points. First, with more time and computational power, it could be interesting to solve, for example, 100 instances of each variant of the problem in order to confirm the trend we observed in our experiments with a larger sample of data.
Secondly, real-world data could be collected and processed to evaluate if our conclusions materialize in real business applications. A third point could be to take into account the willingness of a company to reduce its GHG emissions. For example, one could model different kinds of routes that would be more or less fuel-consuming. The GHG emissions will now be present in the objective function of the problem. In this case, the company would select the suppliers not only according to the cost but also the GHG emissions induced by visiting these selected suppliers. It could be meaningful to investigate to what extent it could influence the occurrence of the RE.
Finally, the time variable could also be taken into account. As a result, the decision of a long-term investment in a new and better fuel-efficient vehicle could be discussed. For a given fixed cost, the company could invest in this vehicle. In this case, it will either lower the fuel consumption and transport cost of the firm or induce more driving to visit other suppliers. Thus, the potential savings could be partially offset and a RE could occur.

To sum up, with this thesis, we were able to highlight the variables and mechanisms that drive the occurrence of RE in transportation by using a simplified model. Significant conclusions could be drawn from the experiments and the results can be easily transferred to real-life business applications. Furthermore, given the increasing need to tackle climate change and the lack of popular awareness about the concept, we are confident that more and more studies discussing the RE as well as the possible solutions to mitigate it will arise.

# Appendices

# Appendix A

# AIMMS Code

```
Model Main_Model_TPP {
  DeclarationSection Declaration_Sets {
    Set Vertex {
      SubsetOf: Integers;
      Index: i, j;
      Definition: ElementRange(from:1, to:10);
    }
    Set Suppliers {
      SubsetOf: Vertex;
      Definition: ElementRange(from:2, to:10);
    }
    Set Products {
      SubsetOf: Integers;
      Index: k;
      Definition: ElementRange(from:1, to:1);
    }
    Set Vehicles {
      SubsetOf: Integers;
      Index: v;
      Definition: ElementRange(from:1, to:1);
    }
  }
  DeclarationSection Declaration_Parameters {
```

```
  Parameter x_Coordinate {
    IndexDomain: i;
  }
  Parameter y_Coordinate {
    IndexDomain: i;
  }
  Parameter distance {
    IndexDomain: (i,j);
    Definition: round( sqrt( (X_Coordinate(i) - X_Coordinate(j))^2 +
  (Y_Coordinate(i) - Y_Coordinate(j))^2 ),3 );
  }
  Parameter purCost {
    IndexDomain: (i,k)| i <> 1;
    Definition: round(Num(k)/distance(1,i),2);
  }
  Parameter capSup {
    IndexDomain: (i,k) | i <> 1;
  }
  Parameter capVehicle {
    IndexDomain: v;
    Definition: sum[k,dem(k)];
  }
  Parameter fuelEff;
  Parameter dem {
    IndexDomain: k;
  }
  Parameter Num {
    IndexDomain: k;
  }
}
DeclarationSection Declaration_Variables {
  Variable w {
    IndexDomain: (i,j,v);
    Range: nonnegative;
```

```
  }
  Variable x {
    IndexDomain: (i,j,v);
    Range: binary;
  }
  Variable y {
    IndexDomain: (i,v);
    Range: binary;
  }
  Variable u {
    IndexDomain: (i,v);
    Range: nonnegative;
  }
  Variable z {
    IndexDomain: (i,k,v);
    Range: nonnegative;
  }
}
DeclarationSection Declaration_Objective_Function {
  Variable ObjFunc {
    Range: free;
    Definition: ProcurementCost + TransportCost;
  }
  Variable ProcurementCost {
    Range: free;
    Definition: sum[(i,k,v),purCost(i,k)*z(i,k,v)];
  }
  Variable TransportCost {
    Range: free;
    Definition: sum[(i,j,v),distance(i,j)*x(i,j,v)*fuelEff/100];
  }
  Variable TotalDistance {
    Range: free;
    Definition: sum[(i,j,v),x(i,j,v)*distance(i,j)];
```

```
    }
    MathematicalProgram MinCost {
      Objective: ObjFunc;
      Direction: minimize;
      Constraints: AllConstraints;
      Variables: AllVariables;
      Type: MIP;
    }
  }
  DeclarationSection Declaration_Constraints {
    Constraint BigMFlow {
      IndexDomain: (i,j,v);
      Definition: w(i,j,v)<=sum[k,dem(k)]*x(i,j,v);
    }
    Constraint FlowNode1 {
      IndexDomain: (j,v);
      Definition: w(1,j,v) = 0;
    }
    Constraint FlowArrival {
      Definition: sum[(i,v), w(i,1,v)] = sum[k,dem(k)];
    }
    Constraint FlowRegular {
      IndexDomain: (i,v) | i IN Suppliers;
      Definition: sum[j, w(j,i,v)] +  sum[(k), z(i,k,v)] = sum[j, w(i,j,v)];
    }
    Constraint ArrivalArcs {
      IndexDomain: (j,v);
      Definition: sum[(i),x(i,j,v)] = y(j,v);
    }
    Constraint DepartureArcs {
      IndexDomain: (i,v);
      Definition: sum[(j),x(i,j,v)] = y(i,v);
    }
    Constraint CapacitySupplier {
```

```
      IndexDomain: (i,k,v);
      Definition: z(i,k,v)<= capSup(i,k)*y(i,v);
    }
    Constraint AvailableQuant {
      IndexDomain: (i,k);
      Definition: sum[v,z(i,k,v)] <= capSup(i,k);
    }
    Constraint CapacityVehicle {
      IndexDomain: v;
      Definition: sum[(k,i),z(i,k,v)] <= capVehicle(v);
    }
    Constraint Demand {
      IndexDomain: k;
      Definition: sum[(i,v),z(i,k,v)] =  dem(k);
    }
    Constraint SubTour1 {
      IndexDomain: (i,j,v) | j <> 1;
      Definition: u(i,v) - u(j,v) + (Card(Vertex)-1)*x(i,j,v) <= (Card(Vertex)
   - 2);
    }
    Constraint SubTour2 {
      IndexDomain: (i,v) | i <> 1;
      Definition: u(i,v)<=Card(Vertex)*y(i,v);
    }
    Constraint SubTourNode1 {
      IndexDomain: v;
      Definition: u(1,v)= 1;
    }
  }
  DeclarationSection Declaration_MultipleIteration {
    Set iterations {
      SubsetOf: Integers;
      Index: n;
      Definition: ElementRange(0,9);
```

```
    }
    Set instances {
      SubsetOf: Integers;
      Index: m;
      Definition: ElementRange(1,10);
    }
    Parameter inst;
    Parameter f_0 {
      InitialData: 40;
      Comment: {
        "! Initial fuel efficiency"
      }
    }
    Variable f_n {
      IndexDomain: n;
      Range: free;
    }
    Variable TotalCost_n {
      IndexDomain: n;
      Range: free;
    }
    Variable Procurement_Cost_n {
      IndexDomain: n;
      Range: free;
    }
    Variable Transport_Cost_n {
      IndexDomain: n;
      Range: free;
    }
    Variable DistanceTraveled_n {
      IndexDomain: n;
      Range: free;
    }
  }
```

```
Procedure MainExecution {
  Body: {
    for (m in instances) do

      ! Data generation
      x_Coordinate(i) := round(Uniform(1,500),2);
      y_Coordinate(i) := round(Uniform(1,500),2);
      dem(k) := round(Uniform(20, 100));
      num(k) := round(Uniform(500,2000));
      capSup(i,k) :=
 round(Normal(2*dem(k)/Card(Suppliers),2*dem(k)/(Card(Suppliers)*4)));

      for (n in iterations) do

      ! Assign a different value to fuelEff at each iteration
      ! At each iteration the fuel efficiency improves by 10%, (f_0
 decreases by 10%)
      f_n(n) := f_0*Power(1-0.1,n);
      fuelEff := f_n(n);

      ! Solve the problem
      solve MinCost;
      ! Save the required outputs
      TotalCost_n(n) := ObjFunc;
      Procurement_Cost_n(n) := ProcurementCost;
      Transport_Cost_n(n) := TransportCost;
      DistanceTraveled_n(n) := TotalDistance;
      endfor;
      ! Print the desired output in a spreadsheet
      if axll::WorkBookIsOpen("Book1.xlsx") then
             axll::SelectWorkBook("Book1.xlsx");
      else
             axll::OpenWorkBook("Book1.xlsx");
    endif;
```

```
    axll::SelectSheet(SheetName : "Sheet"+ FormatString("%i", m));

    ! f_n Table
    axll::WriteTable(f_n(n), "A2:A11", "", "B2:B11");

    ! Distance Traveled Table
    axll::WriteTable(DistanceTraveled_n(n), "D2:D11", "", "E2:E11" );

    ! Transport Cost Table
    axll::WriteTable(Transport_Cost_n(n), "G2:G11", "", "H2:H11" );

    ! Procurement Cost Table
    axll::WriteTable(Procurement_Cost_n(n), "J2:J11", "", "K2:K11" );

    ! Total Cost Table
    axll::WriteTable(TotalCost_n(n), "M2:M11", "", "N2:N11" );

    endfor;
  }
 }
 Procedure RunSingleProblem {
  Body: {
    ! Data generation
     x_Coordinate(i) := round(Uniform(1,500),2);
     y_Coordinate(i) := round(Uniform(1,500),2);
     dem(k) := round(Uniform(20, 100));
     num(k) := round(Uniform(500,2000));
     capSup(i,k) :=
  round(Normal(2*dem(k)/Card(Suppliers),2*dem(k)/(Card(Suppliers)*4)));
     fuelEff := f_0;
    solve MinCost;
  }
 }
}
```

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