Zafeiris Kokkinogenis

Incentive Mechanisms and Policy Evaluation on Open Multi-Agent Systems: Towards Social-Aware Transportation Systems

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A dissertation submitted to the
Faculty of Engineering, University of Porto
in partial fulfillment of the requirements
for the degree of
Doctor of Philosophy in Informatics Engineering

Supervisor: Rosaldo J. F. Rossetti, PhD
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To

Ana,

Sunshine,

Ruca,

Pretolas,

Sima,

Vampyrela,

Branquinho,

Amarelotas,

Pulga,

Pop-corn.

Thank you for being there for me when I needed you most.

Abstract

Incentive Mechanisms and Policy Evaluation on Open Multi-Agent Systems: Towards Social-Aware Transportation Systems

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Generally speaking, a large-scale socio-technical system is formed up of individual entities that are distributed along with the system's space and act asynchronously in their decision-making processes. Each of the individuals bears its own goals and tends to behave rather "selfishly" and "greedily" to maximise self-welfare utilities. However, this characteristic will generally affect negatively the global efficiency and the *designed* (expected) emergent behaviour of the system. Indeed, private road transport imposes negative externalities on society, such as road capacity restrictions, accidents, congestion, etc. An efficient mobility model must take into account the real costs of transport, and its regulatory framework will need to produce the conditions for people to make sustainable transport choices. Economic theories offer two types of instruments for addressing the problem of transport externalities: command-and-control and incentive-based policies.

Command-and-control policies are government regulations which force users to change their behaviour. In that sense, recent approaches to optimise the traffic network throughput and reduce traffic congestion basically rely on "road pricing". However, this approach ends up penalising the user and creating social inequalities as it imposes a tax to be paid. Only those who are insensitive to the price will benefit. Also, a population may not be responsive to the defined penalties, and thus, the regulation may not be efficient.

On the other hand, an approach that has gained the community's attention is based on the implementation and design of incentive schemes in *public policy*. Incentives are seen as those external measures that try to motivate a behavior change towards the objective of the system. It appears to be a "fairer" vision, as it does not discriminate the user but rather tries to bring the society into equilibrium.

The domain area on which this PhD thesis is focused concerns open and competitive multi-agent systems, such as the Intelligent Transportation Systems (ITS) and the electricity markets. This thesis intends to address the issue of whether or not incentive-centred designs can favour the emergence of social-aware behaviour in agents that have selfish tendencies for a (global) optimal evolution of a socio-technical system. Traditional transport planning tools using the four-step model combined with standard economic appraisal methods are not able to provide such analysis. Instead, a multi-agent system (MAS) social simulations can be used as it is argued in the literature of complex systems.

Keywords: *Multi-Agent Systems, Incentive Mechanisms, Resource Markets, Policy Evaluation, Traffic Simulation.*

Resumo

Mecanismos de Incentivo e Avaliação de Políticas em Sistemas Multiagentes Abertos: em direção a Sistemas de Transporte Socialmente Conscientes

Zafeiris Kokkinogenis

De um modo geral, um sistema sociotécnico de larga escala é formado por entidades individuais que são distribuídas, assim como pelo espaço do sistema, e que atuam de forma assíncrona em seus processos de tomada de decisão. Cada um dos indivíduos tem seus próprios objetivos e tende a se comportar de maneira egoísta e gananciosa para maximizar a utilidade do seu bem-estar. No entanto, essa característica geralmente afeta negativamente a eficiência global e o comportamento emergente (esperado) do sistema. De fato, o transporte rodoviário privado impõe externalidades negativas à sociedade, como contragimentos nas estradas, acidentes, congestionamentos, etc. Um modelo de mobilidade eficiente deve ter em consideração os custos reais do transporte e a sua estrutura reguladora precisará criar as condições para as pessoas fazerem escolhas sustentáveis de transporte. As teorias economicas oferecem dois tipos de instrumentos para abordar o problema das externalidades de transporte: políticas de comando e controle e baseadas em incentivos.

Políticas de comando e controle são regulamentos governamentais que forçam os utilizadors a mudar seus comportamentos. Nesse sentido, abordagens recentes para otimizar o fluxo da rede de tráfego e reduzir o congestionamento são basicamente relacionadas com os preços de utilização das estradas. No entanto, essa abordagem acaba por penalizar o utilizador, criando desigualdades sociais pois impõe um imposto a ser pago. Somente quem é insensível ao preço será beneficiado. Além disso, uma população pode não responder às sanções definidas e, portanto, o regulamento pode não ser eficiente.

Por outro lado, uma abordagem que tem merecido a atenção da comunidade é baseada na implementação e no desenho de esquemas de incentivos em políticas públicas. Os incentivos são vistos como medidas externas que tentam motivar uma mudança de comportamento em direção ao objetivo do sistema. Parece ser uma visão mais justa, pois não discrimina o utilizador, mas tenta trazer a sociedade para o equilíbrio.

A área de domínio em que esta tese de doutorado é focada são os sistemas multiagente abertos e colaborativos, tais como os Sistemas Inteligentes de Transportes (ITS) e mercados de energia. Esta tese pretende abordar a questão de determinar se os projetos centrados em incentivos podem ou não favorecer o surgimento de comportamentos socialmente con-

scientes em agentes que têm tendências egoístas para uma evolução ótima (global) de um sistema sociotécnico. As ferramentas tradicionais de planeamento de transporte, usando o modelo quatro-passos, combinadas com os métodos tradicionais de avaliação econômica, não são capazes de fornecer essa análise. Em vez disso, as simulações sociais baseadas em sistema multiagente (MAS) podem ser usadas, como é discutido na literatura de sistemas complexos.

Palavras-chave: *Sistemas Multiagentes, Incentivos, Avaliação de Politicas, Mercados, Recursos, Simulação de Transportes.*

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Contents

List of Tables

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List of Acronyms

ASL Agent speak language

AS Appliance Scheduler

AI Artificial Intelligence

ATS Artificial Transportation System

AutoML Automated Machine Learning

BDI Belief, Desire and Intention

BPMN Business Process Modelling Notation

BPM Business Process Modelling

CFP Call For Proposal

CAV Connected Automated Vehicle

CI Climate Intelligence

DSM Demand-Side Management

HEM Home Energy Management

ITS Intelligent Transportation Systems

IoT Internet of Things

IoV Internet of Vehicles

MAS Multi-Agent System

MARL Multi-Agent Reinforcement Learning

ResMAS Resource-based Market Agents Systems

V2I Vehicle-to-Infrastructure

V2V Vehicle-to-Vehicle

VFC Vehicular Fog Computing

XAI eXplainable Artificial Intelligence

Chapter 1

Introduction

The rapid and ever-increasing population and urban activities has imposed a massive demand to urban transportation systems. However, most of the urban areas were not prepared for such hasty development which led to weak and defective metropolitan transportation systems. Therefore rapid and effective interventions in traffic management and planning are needed to prevent their negative impact on the city's social and economic welfare.

Yet, an important characteristic to bear in mind is that the domain of mobility (transportation of both people and goods) presents an inherent complexity. It involves a vast number of heterogeneous entities either in structure or in behaviour such as, vehicles, pedestrians, traffic infrastructures and ICT devices among others, which can interact reflecting social behaviours that go from coordination and collaboration to competition. Moreover, a high degree of uncertainty and dynamism especially when considering the urban context is uncovered. To address the rising issues of these new trends a new generation of mobility systems emerged with the advent of what has been coined Intelligent Transportation Systems (ITSs), forcing architectures to become adaptable and accessible by different means so as to meet different requirements and a wide range of purposes. The idea of such systems is to ensure the efficient utilisation of the available road capacity by controlling traffic operations and influencing drivers' behaviour by providing proper information and stimuli.

The explosion of the computing technology in terms of applications experimented in the last couple of decades brought together expertise from different scientific and technical disciplines giving birth to new computing and communication paradigms. A new type of systems coined as socio-technical arose from such mutual conjunctions where people and technology live in mutual symbiosis. The transportation and, generally speaking urban domain, could not be impermeable to such revolution. Indeed, it proves to be a valid field where new social and technological paradigms emerge. A new concept has been conceived to deal with this revolution, the so called smart mobility systems (SMS). The notion of mobility systems overcomes ITS limitations; instead of focusing only on the simple processes of transporting goods and persons they become self-conscious in terms of environment, accessibility, equality, security, and sustainability of resources. Smart mobility systems are not meant to replace the advances and benefits of intelligent transportation systems; rather, their objective is to complement them considering mobility from other point of views. While ITS stress on notions such as control and embedded systems, fault tolerance, security, safety, and infrastructures, SMS focus on the emerging opportunistic behaviours, soft-control, market-oriented paradigm, utility, and disruptive innovation. The roles of user and provider are well distinct in the former while they can be exchanged in the latter case. Users, as well as are their preferences, are placed as a central aspect of the urban

systems, forcing architectures to become rather adaptable and accessible to their needs. Therefore, new technologies and methodologies are necessary to support these new models, which motivate this work.

1.1 Motivation

The major effect of this evolution is that the increase in transportation volume generates traffic congestion. In metropolitan areas, traffic congestion is a phenomenon caused by too many vehicles trying to use the same infrastructure at the same time. The consequences are well-known: delays, air pollution, and user dissatisfaction which may lead to risk manoeuvres thus reducing safety for pedestrians as well as for other drivers. The increase in transportation demand can be met by providing additional capacity. However, this might no longer be economically or socially attainable or feasible. Thus, traffic engineering seeks to improve the existing infrastructure, without increasing the overall nominal capacity, by means of an optimal utilization of the available capacity. Traditional approaches as the four-step model do not account for information about user preferences and tend to deal with "management and control" policies. Thus it is not accounted the effect of selfish behavior and "free-riding" from self-interested agents that have reasons to only improve their individual utilities rather than the collective social welfare. The strategic interactions of such self-interested agents lead systems to (Nash - Wardrop in the case of transportation domain) equilibrium that can be highly inefficient from a social point of view. An example of such situation is reported in the Braess paradox, where the addition of a new road leads the network into a Nash equilibrium with an increase to the overall social cost. Similar is the concept of control strategies in [PDD+03]. Authors illustrate the main reasons for infrastructure deterioration due to traffic congestion and discuss a comprehensive overview of proposed and implemented control strategies provided for three areas: urban road networks, freeway networks, and route guidance. One of the conclusions the work presents is that any substantial improvements achieved thanks to application of control methods may be countered to some extent due to latent (induced) demand, i.e., due to drivers motivated to use their cars (rather than other transportation means). As control strategies are not sufficient enough by themselves, complementary approaches need to be sought and implemented to surrogate traditional traffic control. One possible suggestion proposed in the literature is through influencing user behaviour. Typically road pricing has been seen as a command-and-control approach, a penalization for the users as they have to pay an additional tax. This is mostly because current pricing schemes are rigid with fixed values independently of the system conditions [Lev10].

Recent approaches to optimize the traffic network throughput and reduce traffic congestion take road pricing approaches to another level, considering the existing traffic conditions and adapting the price accordingly (e.g. [BM17, MJS+19]). In this sense the system incentivizes through a soft-control approach the correct usage of the network. An approach that has gained transportation & traffic community's attention is based on the implementation and design of policies based on incentive schemes. Such incentive schemes can be based on the concept of tradable travel credits [NY13]. Incentives are seen as those external measures that try to motivate a behaviour change towards the objective of the system. It appears to be a more "fair" vision, as it does not discriminate the user but rather tries to bring the community into an equal level.

1.2 Problem Statement

The main problem emerging in rather dynamic and competitive environments is that individual user's do not align to system's global goal. This happens due to the lack of proper social coordination among the users' actions that gives rise to undesired emergent dynamics such as congestion, in the traffic domain, or hit peak loads in electricity grids. This is observed in most of the socio-technical domains, that are systems that share social and technological characteristics with the aforementioned areas and are composed of numerous and strongly heterogeneous entities. To tackle this kind of issues for achieving social coordination when allocating resources and making decisions in environments with multiple agents, each seeking to maximize individual utility, the Multi-Agent System (MAS) community has come up with concepts such as organizations, norms and other collective decision mechanisms (e.g. negotiation, voting, auctions, etc.) to favour a fluid operation of the system. Within the MAS literature, agent organizations in terms of electronic institutions and normative systems, resembling real-world institutions that regulate interactions in a society, have been studied as regulatory structures, in order to circumscribe the emergence of discontinuities due to the diversity (or selfishness) of goals expressed in a system among its entities. However, there are situations in which the aforementioned approach does not obtain the expected results (or behaviours) as the population of the agents might still have some degree of freedom which can lead to inefficient evolution of the system or the population could not be sensitive either to the penalties or to the rewards applied as result of norm violation.

The current trend in the multi-agent systems field is to emphasize on the openness of systems, their ad-hoc integration capability, and to capitalize on their syntactic and semantic interoperability. In open environments, we can no longer assume that the agents are cooperative. The agents in these systems can have their own, sometimes partially or completely antagonistic goals and they often compete for the shared resources or opportunities.

Abstracting to higher levels, socio-technical systems, such as Intelligent Transportation Systems (ITSs) and energy markets, perfectly reflect the openness and "selfishness" exposed in open multi-agent systems. For example, an unknown set of heterogeneous commuters populating the system and pursuing their own goals can join or exit the system; there is no direct control of their behaviour. Traffic is another example, as such a system presents an inherent complexity; a large number of interacting elements, characterized by behaviours that emerge as a result of often nonlinear spatial-temporal interactions among its elements at different levels of organization, and the properties of which is not simply the sum of the proprieties of the system's elements. Indeed, thousands of commuters daily define their planned activities, mostly requiring trips to be performed among different places of origins and destination. These scenarios imply agents will make autonomous decisions about the route to perform and the departure time selection, learning from their former experiences and influencing each other in both positive and negative ways. In such environments, we must ensure that the system as a whole will autonomously maintain its sustainability and efficiency, that self-interested agents will be able to agree at least on some goals and that the coordination will leverage their capabilities.

So we need to devise social coordination mechanisms that can influence the agents to adopt a social-aware behaviour towards a social "welfare equilibrium" state. From the

previous discussion, one can defend incentives as a good mechanism to motivate social-aware behaviors in the individuals that work for the overall benefit of the system. One application of such incentives is to charge taxes, that is eliciting monetary fees from users that will affect their perspectives, and thus preferences, over the available actions. Another approach to influence user behavior is to reward actions that are preferential from the system designer's perspective.

This thesis therefore addresses the conceptualization and implementation of incentive mechanisms as a social coordination method in the scope of multi-agent systems operating in dynamic and competitive environments; more specifically, the approaches herein proposed are inspired and conceptualized upon the interpretation of the specific domains of traffic and transportation systems and energy markets in urban settings. In this perspective we consider the following hypothesis:

Hypothesis: Introducing incentive designs in dynamic and competitive environments leverages the system propensity to yield social coordination among agents.

In the quest of addressing the aforementioned hypothesis, an effort has been put on studying the applicability of incentive mechanisms or policies towards achieving social coordination. More specifically, this dissertation aims to pursue the following research questions:

- *RQ1: Are market structures efficient enablers for achieving social coordination in Multi-Agent Systems?*

  Markets are economic ecosystems where two or more parties engage in resource exchange. Their main role is to coordinate the flow of a given demand for a given supply of resources. We will present a conceptual model of resource-based markets based on the MAS paradigm, and show how it is possible to create different soft regulation policies (incentive designs) that promote social coordination in energy systems with different hierarchies. We will instantiate the resource-based market model to a home energy management system in terms of a formal model. We use simulation to empirically assess regulation policies to achieve sustainability.

- *RQ2: Can a voting strategy/method be used to promote social welfare?*

  Analyzing the agents' utility distribution given a voting rule and a social welfare function it seems to be possible. We will provide evidence of how such strategies can be effectively implemented using simulation.

- *RQ3: Can auction strategies/methods be used to promote social welfare?*

  Auctions is a well known mechanism for social coordination in resource allocation problems. Analyzing the agents' utility distribution given an auction method and a social welfare function we show it is possible to apply such mechanisms to the domains under study. We will provide evidence of how they can be effectively implemented using simulation.

- *RQ4: Is social welfare a good metric to evaluate actionable policies towards the implementation of sustainable systems?*

To address this question a decision-support framework is conceived to support the evaluation of actionable policies to yield social coordination exploring the concept of climate intelligence to leverage sustainability. The platform includes model-driven and data-drive models and envisages gamification as a means to implement incentives at the individual level. The system considers multiple actors' perspectives and may be seen from multiple resource perspectives.

1.3 Expected Contributions

This dissertation studies and explores the applicability of incentive mechanisms as a social coordination method (towards social welfare) in MAS operating in dynamic and competitive environments. More specifically the study finds inspiration in the domains of traffic and transportation systems and energy markets. These two domains can very intuitively be interpreted as multi-agent systems operating in open dynamic and competitive environments, offering a plethora of different and rich scenarios with which to test the models and approaches conceived. To reach this target, we have performed the following efforts, which constitute important contributions of this dissertation.

1. Review of the literature on concepts related to incentive mechanisms and policy assessment. Incentives are policies introduced by the system/environment to yield an efficiency metric for the desirable outcome. Different incentive mechanisms are considered either positive (rewards) or negatives (penalties). Policy-making assessment is mainly related to the tools available to assess the outcomes of policies. Game theory is also approached to underlie both the conceptualization of incentive mechanisms and how such incentives embedded in the design of policies can effectively be evaluated.

2. Design of a modeling approach that captures the main concepts and processes related to resource-driven markets, in which actors, although seeking to maximize their own profit, are also sensitive to possible incentives from e.g. regulating entities that can persuade in favour or against their choices. The modelling approach is generic and able to represent different market structures.

3. Design of a simulation framework to test with social coordination mechanisms in real-world settings. Such a simulation-based approach is demonstrated in the domain of vehicle communication settings to evaluate how platoon formation can result from social coordination mechanisms and social welfare performance metrics from the perspective of the whole system.

4. Design of assessment approaches to evaluate auction-based social coordination incentives. We are rather interested in evaluating whether auction-based approaches can be used as a social coordination mechanism. We apply this approach extending the real-world settings of the previous chapter involving platoon formation relying on auction mechanisms.

5. Design of a decision-support perspective to underlie climate-intelligence actionable recommendations. Specification of the architecture of a climate-intelligence decision-support system to design, test, and evaluate actionable policies in domains whose efficiency and sustainability is heavily dependent on how resources are competed by the different actors. To consider the various components of this framework we propose a number of methodological approaches we devised for analyzing a number of case studies to which this framework is instantiated.

1.4 Thesis Outline

The contributions outlined in the previous section are described in terms of five chapters. All chapters contribute in analyzing the thesis's *hypothesis*. Chapter 2 reviews incentive schemes and policy assessment from the perspective of the MAS paradigm. Chapter 3 addresses *research question RQ1* formalizing the energy domain as a hierarchy of autonomous market structures. Chapter 4 considers *research question RQ2* by presenting an integrated simulation tool for experimenting with collective decision-making for platoon coordination in presence of self-interested autonomous vehicles. Chapter 5 addresses *research question RQ3* analyzing the viability of auction mechanisms to enable vehicular coordination in platoon formations. Chapter 6 deals with *research question RQ4* considering a Climate Intelligence support system to provide actionable recommendation by assessing policies in electrified mobility.

1.5 Publications Underlying the Chapters

The following list gives an overview of the publications originating each of the chapters in this thesis:

Chapter 3 is based on works appeared in the *Proceedings of the* 15th *International Conference on Practical Applications of Agents and Multi-Agent Systems (PAAMS'17)* [RKC+17] and in the *Proceedings of the 2021 IEEE International Smart Cities Conference (ISC2)* [MRK21].

Chapter 4 has been published in the journal of *Simulation Modelling Practice and Theory (98)* [TdK20]

Chapter 5 appears in the textitProceedings of the 2019 IEEE Intelligent Vehicles Symposium (IV) [KTdR19]

Chapter 6 is based on publications appeared in the *EEE Intelligent Systems 28(4)* [RAKG13], *Proceedings of the* 16th *International IEEE Conference on Intelligent Transportation Systems (ITSC 2013)*[MKS+13], *Proceedings of the* 17th *International IEEE Conference on Intelligent Transportation Systems (ITSC 2014)* [KMR+14], and *Proceedings of the* 19th *International IEEE Conference on Intelligent Transportation Systems (ITSC 2016)* [SKdS+16]

Chapter 2

A Review of Incentive Mechanisms and Policy Evaluation Methods in Open Multi-Agent Systems

2.1 Introduction

Policy generally speaking, is defined as course-of-actions, plans or strategies by which a system manager representing a government or an organizations translate the system's vision into programs and activities. Policy is conceived as a set of principles that will orient and/or condition decisions and actions of the individuals that operate in a given context, especially in what concerns the uses of resources available in that context [Eas65]. Hill and Frederic in [HV14] explains public policy in a given society as concerning the uses of resources that are considered to be public in that society (and usually being issued by some authority of that society). As policy making process is intended the way to conceive the structure and form of operation of public policies, and explains how public policies are created and put to operation.

Some of the models of public policy process are sequential; the process of creation and application of public policies is envisaged as a series of steps performed, at each time, by one of the different actors (or group of actors) involved in the process. Policy-making, as a kind of rational decision-making, includes two different types of intellectual activity: knowing and evaluating. A typical way to depict the sequential cycle of steps involved in such models is as follows [HV14]:

- Identification and formulation of the issue to be solve through the issue and implementation of a public policy;
- Formulation and comparative analysis of various possible alternative policies able to solve the problem;
- Choice of one of those policies for implementation;
- Implementation of the chosen public policy;
- Evaluation of the effects of the implementation of the public policy, and possible adjustment of the policy, to improve results and reduce negative effects (thus returning the process to step 1).

Van Engers et al. in [vEvHS11] characterize policy-making (policy-design) into a policy eld theory and a policy effects theory; one theory dedicated to a problem and the other to a solution space. A policy field theory will answers on questions like: which actors and factors do create problems and possibilities in a certain policy field, which require the attention of the policy makers. As such, a policy field theory has a causal component and a normative component. On the other side, policy effects theory describes the effects of possible actions that are assumed to provide a solution to the problem at hand. The connection between these actions and the problem is through factors that have a causal relationship to the problem. The policy-making process is aimed at finding and deliberating possible alternative solutions/ actions.

Van Wee in [vW09] distinguishes six general criteria for policy intervention to be taken into account during the decision-making process:

- Effectiveness: does the policy do what it supposed to do?
- Efficiency: are assessed the cost-effectiveness and the cost-to-benefit ratio indicators;
- Equity: are there winners and losers because of the policy introduction?
- Ease of implementation;
- Flexibility in adapting the policy;
- Long-term robustness: policy is 'no-regret' under uncertain long-term developments that could have a major impact on society;

2.2 Theory of Incentives

Policy-makers have two broad types of instruments, borrowed from economics, available to achieve a desired outcome. They can use traditional regulatory approaches (sometimes referred to as command-and-control approaches) or they can use incentive-based (or market-based) policies that try to create a motivation to behaviour changes in individuals. The study of incentive structures is central to the study of all economic activities (considering the cases individual decision-making or the one of co-operation and competition within a larger institutional structure). A well-known problem that includes the essence of incentive issues is the one of delegating a task to an agent who has different objectives than the principal who delegates this task when information about the agent is imperfect. Here information is considered the so-called type of an agent that refers to, e.g., skills or opportunity cost. The agent may not reveal his type to the principal or he may even provide false characteristics. Therefore, an aspect of paramount importance within this area is uncertainty due to a lack of information. The three main types of principle-agent problems are moral hazard, adverse selection, and signaling. Here, the agent has either (i) private information concerning actions that occur after the signing of a contract, (ii) private information concerning his type before the composition of the contract, or (iii) the ability to send information to the principal during the game. This is what in literature is described as the principal-agent problem [LM09].

The principal-agent problem discusses the interactions between two parties, an agent (or follower) and a principal (or leader), where the action(s) made by the agent imposes externalities on the principal. It is intuitive that the principal will want to influence the agent's actions in order the latter to align with the former's objectives(s). Another important part of the problem definition in incentives theory is the participation constraint or bailout option of the follower, which allows him to withdraw from participating in the game in case the leader proposes a contract that leaves the follower with an insufficient performance. The principal-agent problem is a special case of the general problem of mechanism design that is, designing a game form that will implement a desired outcome as equilibrium of the game [CH00, HCF15]

Classic Mechanism Design (MD) (or implementation theory) is the area of microeconomics and game theory concerned with how to design systems that involve multiple self-interested individuals (agents) each with private information about their preferences, using tools developed by game theory analysis, such that certain system-wide properties emerge from the interaction of the constituent components [Mas08, How18, HZZS16]. Why is this so "important"?

In society, in a system, individuals have information about their resources, desires and preferences. And they choose actions for producing, redistributing, and consuming those resources. In markets and other institutions, individuals' actions may depend on others' information as it has been communicated in the market or institution. The institutions are to be used as mechanisms for communicating people's information and coordinating people's actions. A good social institution is decided upon how it performs in this communication and coordination role. If we do not like the performance of our current institutions, then we may want to reform them, to get an institution that implements some desired social plan, where a social plan is a description of how everyone's actions should depend on everyone's information [RDSF19, Mye08].

A mechanism design considers a set of outcome rules and actions, and a set of players (agents). The mechanism is designed so that the agent's preferred strategies are such that the outcome (or social goal) corresponds to the outcome desired by a system planner (a society), this is interpreted as efficient use of the system (i.e. existing transport infrastructure). In a mechanism design problem one can imagine that each agent holds one of the inputs to a well-formulated but incompletely specified optimization and that the system's wide goal is to solve the specific instantiation of the optimization problem specified by the inputs [NR01, Rou10]. Consider for example a network routing problem in which the system-wide goal is to allocate resources to minimize the total cost of delay over all agents but each agent has private information about parameters such as message size and its unit cost of delay. A typical approach in mechanism design is to provide incentives for example with suitable payments to promote truth revelation from agents such that an optimal solution can be computed to the distributed optimization problem.

A less formal definition of incentives can be described through motivation; a critical dimension of capacity, defined as the ability of people, institutions and societies to perform functions solves problems and set and achieves objectives. Incentives and incentive systems are fundamental to developing capacities and to translating developed capacities into better performance" [BR03]

Motivation refers to the initiation, direction, intensity and persistence of behaviour. Incentives on the other hand are external measures that are designed and established to influence motivation and behaviour of individuals, groups or organizations. Incentives can be classified according to the different ways in which they motivate agents to take a particular course of action. We choose a classification based on the types of stimuli that encourage agent cooperation. In Figure 2.1, this classification approach initially identifies two large branches: *Financial* and *Non-financial* incentives.

In Financial-based schemes, agents pay to obtain services and get rewarded for the ones they provide. Payment is compensation for the resources made available when performing collaborative operations. The distinction between *Direct Monetary compensation* and *Indirect tradable token schemes* is based on the established monetary unit in a system. A monetary compensation involves an economic transaction of a monetary unit, while a tradable token scheme involves an equivalent in value quantity of an item that is valid within a specific financial ecosystem and for a specific range of services. In any case, both schemes lead to an increase in the economic power of the participant. Furthermore, both direct and indirect benefits can be predetermined by some criterion and can be set or variable over time, for each agent or the entire system, but must represent the true cost incurred by the service provider.

On the other hand Non-financial incentives don't involve transactions of economic values among agents but mostly are focused on social exchanges, auto-motivation, or easy alterations of the environment. Social exchange is based on the reciprocity a type of interaction in which one agent acts on behalf of another and is rewarded with an action in reciprocation either immediately or in the near future [RL14]. Typically there are three incentive patterns identified: *Reciprocity-based*, *Intrinsic-based*, *Nudging*:

- Entities opt to cooperate in reciprocity-based systems based on their knowledge of the requesters' current or previous collaboration. An entity either gives service to contributors and defect non-contributors or selects its providers to improve the likelihood of successful contact. Reciprocity-based schemes are either *Exchange-based* or *Reputation-based*. In the former, agents exchange services or resources among them. In the latter, incentive schemes rely on reputation value to choose whether or not to engage with an entity. The reputation value is computed using prior behavior data and represents the likelihood of cooperation in the upcoming engagement. One agent's trust in another is twofold: the interaction is helpful for the service provider because it trusts in sharing the same objectives as the consumer, or it believes in boosting the cooperativeness of other agents. This results in two additional patterns (see [ON03]); the *collective pattern*, where agents' cooperation stems from being members of the same collective, and the *community pattern*, where the cooperation is based on the reputation gained by acting as provider to other agents of the community.

- Nudge theory is a behavioral economics concept that promotes positive reinforcement and indirect recommendations as approaches to affect the group or individual behavior and decision-making for achieving compliance without forbidding other alternatives or significantly affecting economic incentives [Sug09]. Nudges are small alteration in the environment that are easy and inexpensive to implement. Burr et al. explaining in [BCL18] how customized targeting algorithms may employ persuasion

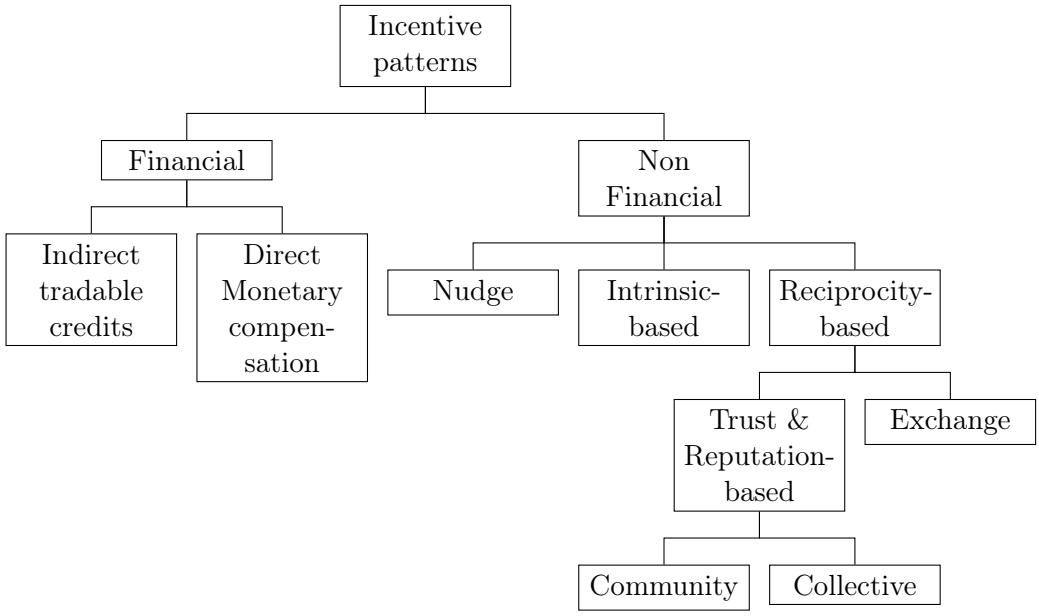


Figure 2.1: "Taxonomy of incentive patterns for cooperation"

and psychometrics to affect individual and group behavior, sometimes in unforeseen ways. Another example is informational nudging, which is described as conveying manipulated and sometimes false information about alternatives to a decision maker in order to influence its decision [CL16].

- The intrinsic pattern arises from a drive of its own motivated from within an individual for a state of inherent satisfaction and is thus not focused on the outcome of an activity ([JH08]).

2.3 Policy and Incentives in the Transportation Domain

Policy-making is particularly interesting in the transportation domain, as it constitutes a neuralgic area in socio-economic and technical systems. Some transport policies aim at decreasing transport resistance factors (money, time, and effort); other policies try to influence the needs and location of activities or try to improve the environmental performance of vehicles, and so forth. Externalities in the transport area are identified to generate inefficiencies and social-welfare losses. This is based on the fact that people make their decisions considering only marginal private costs and not on marginal social costs, which is a result of market failures. The way of how to internalize the difference between social costs and prices is a challenge for policy-makers traffic/transportation and urban managers. The most important dimensions of external costs are usually found to be congestion, air pollution, accidents, and noise. Santos et al. [SBM$^+$10a, SBT10] extensively review the main road transport externalities and economic policies in transportation. Throughout their study authors has examined the most important negative externalities (accident, road damage, congestion, environmental pollution) and a number of command-and-control and incentive-based policies. Among the policies that have been proposed to attenuate these negative externalities, road or congestion pricing is the major strategy considered. In this

case road pricing aims to internalize the external costs of car traffic. This will increase the welfare of all road users, assuming that the charges will be return to car-users in terms of investments that will improve his/her comfort [SBM+10a, RV06]. In the ideal case, prices are set such that they equal the marginal costs of a trip, including the marginal external costs, providing the maximization of social surplus and welfare (first-best solution). In practice, this will imply that the use of the road system is charged higher at congested periods and congested locations, so that use of the road system at those times/places is discouraged and road users are encouraged to use alternative modes, routes or times. In that sense road (congestion) pricing has become a cardinal point in the transportation economic literature [Lev10, Bly05, BM17, MJS+19, PBMT17, SHR+17, TV09].

These behavioural responses in the road pricing application (that is to be intended as disincentive or negative incentive) lead to an increased efficiency of the transportation systemr [BSM+07]. Pricing, however, is a negative incentive and commuters' public acceptability of such a measure is typically low [RMGK10]. In [BM17] is discussed the possibility of using MD in transportation for implementing social optimal congestion levels. One of the first approach to circumvent this unwillingness has been described in [Kve01] where it has been proposed a theoretic compensation-based mechanism to substitute the fixed road pricing schemes (Pigou taxes). In this mechanism drivers need to announce what how much transport he will demand, and how much he will pay for this to the other, and how much he should be paid to accept the other individuals' choice of transport. Furthermore they have to pay a penalty if they announce a compensation for the chosen level of transport (and hence, the delay) being different from the level of the compensation announced by the agent suffering from the delay.

Both incentives and disincentives (rewarding and charging) may be used to achieve the same goal. In terms of acceptability rewarding appears to be more acceptable by most people than charging. Still it is open issue the effectiveness of both measures [FBM19]. Although intuition suggest that rewarding may be more effective because some car drivers will consider rewarding more attractive, since punishment is bad for effectiveness and a positive incentive makes people happy, this is subjective to whether the drivers population is homogeneous in their preferences and the preferences are known a-priori [FBM19].

Three experimental studies (two in the field and one simulation-based) in transportation have used monetary positive incentives (unlike road pricing schemes that are based on negative incentives) as instrument to influence drivers' behaviour by changing their perceived individual utility function. In Ettema et al. [EKV10] authors suggest the use of positive incentives (monetary and credits) to stimulate changes in travel behaviour of commuters on a congested highway in The Netherlands within the "peak avoidance" project. Their results suggest that both the types of incentives resulted in a considerable reduction of peak car trips of participants. Among the finding of the experiment is that commuters adjust their behaviour when they have flexible work hours, have public transport alternatives and regularly use traffic information. Finally authors observed that when no reward was offered commuters avoiding traffic decreased significantly. Bliemer and Amelsfort [TBEEvD13] perform a comparative analysis of rewarding versus pricing schemes on a road transportation network. The model tries to evaluate the potential of rewarding schemes on traffic conditions, and to forecast network wide effects in the long term by assuming higher participation levels having as case study the peak avoidance project [EKV10]. Merugu et al. [MPR09] describe the INSTANT (Infosys–Stanford Traffic project) raffle-based incentive

mechanism to encourage commuters to commute at less congested times. The proposed scheme has three components: credit allocation, weekly reward draws and credit deduction. Authors sustain that for achieving an improvement in congestion management only a part of the overall population it is necessary to be induced to change its travel behaviour. In that sense their approach is applicable to a sub-population such as a corporation or a neighbourhood. Commuters who modify their behaviour unilaterally will benefit from reduced commute times and have a more comfortable commuting experience.

Goodwin in [Goo08] extensively reviews available evidence on the nature and size of demand responses in passenger transport which would be relevant to setting and achieving carbon reduction targets. The review reveals the variety of travel choices people make. The modal choice is not only between cars and public transport, including the volume and location of travel, but also walking and cycling, driving styles, levels of car ownership, where to live and work and shop, and the type of activities they participate in. Among author conclusions is that exist a very large volume of empirical and case study evidence about the effect of changes in price, speed of travel, quality, information, new infrastructure, better use of existing infrastructure, planning, and other factors which can be influenced by public or private interventions. A common characteristic of those interventions (evidence based on experience is available) is that they often are cost-benefit solutions.

In that sense, a different approach in applying incentives is discussed by Fitzhum [Fit12]. Author evaluates how the combination of providing traffic-related information and monetary incentives to drivers can impact on the congestion intensities under different operational level of a single corridor. Here, the author assumes the existence of a device interface between the network operator and the road user. Information dissemination of traffic conditions is not a new approach as a way to alleviate traffic congestion and has extensively been studied in the context of advanced traveler information systems [WBKS02, LGBE11, B$^+$11, CL16]. However, providing travel information has been applied as measure alone without considering a reward for those travelers how decide to reroute and reschedule their trip. The space of (dis-) incentives it is not only related to pricing schemes and traffic congestion but embraces all the dimensions reported previously in Table 2.1 in order to deliver a sustainable mobility services. This is for example the objective of the SUNSET (Sustainable Social Network Services for Transport) project. The direction followed in SUNSET lies within four types of incentives:

- Real-time travel information (i.e. system provision and peer-to peer exchange);
- Feedback and self-monitoring;
- Rewards and points;
- Social networks.

It is worthy to notice how transportation community started to embrace the influence and potentialities of the social networks to align individual and system objectives. Towards this direction move the works proposed in [HYG$^+$12, HLB$^+$12] that leverage on the use of socials networks and social participation to motivate or to "put pressure on" people to behave in certain ways. An incentive-centred design based on self-monitoring and feedback is proposed by Agerholm in [AWTL08] where it is proposed a mechanism for intelligent

speed adaptation. Similar applications, focus on fuel consumption this time, is currently pursue by the automotive industry. For example, Liimatainen [Lii11] discusses the case of eco-driving incentive scheme based on the fuel consumption to motivate heavy-duty vehicle drivers improving their driving skills. In the I-GEAR project [[MK12] is presented the concept of incentives being provided to drivers in the form of a game. The project do not visualise that one particular type of incentive will work for all drivers. Instead through the contextual examination process the authors try to identify combinations of incentives and motivations can be applied either on an individual or group defined basis.

Although many authors agree that incentive can be a viable solution, it is still remain to establish if they are also effective in large-scale application. Also, it is worthy to realize that so far the proposals of incentives follow a rather vertical approach. That is, an interaction between authorities and users. However some interesting approaches are proposed by the SUNSET [84] and Trucentives [HYG+12] projects initiatives where a horizontal application of incentives is discussed in order to regulate the interactions (and thus incentivize) among users. This last is also interesting because creates a new type of market the possibilities of which have not yet been explored.

2.4 Multi-Agent Systems: Definition, Architecture, Environment

The agent metaphor is based on developments in different computer science areas such as artificial intelligence, distributed systems, and software engineering. It has been strongly motivated by the research results of other disciplines as well, in particular sociology, biology, systems engineering and economics, and many others. These research areas are expressed in multiple features that characterize agents (autonomy, adaptability, reasoning, sociability etc.). Indeed, Multi-Agent Systems notion depicts a framework that is appropriate for many real world systems consisting of a set of interacting autonomously deciding actors.

2.4.1 Definition: What are "Agents" for?

A discussion in research community about how an agent should be defined is open. Nevertheless, over the years, this interest in finding a formal consensus has decreased and emphasis is placed on application domains of the agent paradigm. However, some common characteristics are shared among the different definitions. So, they all agree that an agent denotes an autonomous entity which is placed in an environment and interacts with it and the other agents to achieve specific goals [FG96, RN10, WJ94]. These entities can vary depending on the settings defined such as the environment, e.g., actors in a simulation of artificial societies in contrast to so-called software agents, i.e., systems which are placed in an software environment, like the Internet. Since there is no general definition it can be very helpful to describe some typical properties of an agent ([Jen00, WJ94]):

- Situatedness (and locality): Every agent is situated in an environment; there is an ongoing interaction between the agent and its surroundings. The agent perceives information via sensors and acts on the environment via actuators. This is related to locality, as it can sense and act on those part of the environment that are near to it (or somehow reachable).The definition of the environment depends on the application.

- Autonomy: There is no global control that dictates what actions the agent must take; it dos whatever it is programmed to do based on its current internal state.

- Sociability: agents are able interact with other agents.

- Reactivity: agents sense their environment and they are able to react appropriately to stimuli coming from it.

- Pro-activeness: agents do not simply act in response to their environment; they are able to have goal(s) that they pursue on their own initiative.

Additional characteristics that agents might have:

- Rationality: The notion of agent rationality means that an agent is working towards its personal goals. An agent would always select the action with maximum (expected) outcome with respect to its goals.

- Flexibility: this for an agent means to mediate between reactive behaviour, being able to react to changes in its environment, and deliberation to pursue its goals. A suitable mediation is one of the critical aspects for an agent to achieve its tasks in a (dynamic) environment.

- An agent may be adaptive, by having rules or more abstract mechanisms that modify its behaviours. An agent may have the ability to learn and adapt its behaviours based on its accumulated experiences. Learning requires some form of memory.

2.4.2 Architecture

While a single definition of agent is lacking, many taxonomic descriptions can be found. For instance, Wooldridge distinguishes agents by their decision-making architectures ([Woo09]), Nwana in [Nwa96] classifies agents according to their cooperative and learning properties, and other authors organize by application, function, class, or capability of the agents. Agent model can reach different levels of complexity and functionality, going from a simple reactive to a more complex cognitive structure.

2.4.3 Environment

A multi-agent system is a system that is formed by agents interact each other with purpose to accomplish some goals individually or not; hence, the social dimension of the agent. Modelling such a system we should account not only for the single agent but also for the environment where the agents lives and shares eventually with other agents. Such an environment could consist not only of other agents, but also of resources, infrastructures, obstacles and other entities. Within the environment agent will interact in order to accomplish their individual goals and the overall systems goals, even though this is not strictly necessary. Indeed, the notion of environment pops up with the agent definition due to the strong correlation between them. Weyns et al. in [WOO07] survey the literature of MAS and redefines the environment as "(...) a first-class abstraction that provides the surrounding conditions for agents to exist and that mediates both the interaction among agents and the access to resources". This stresses the fact that the environment is an independent building block in the MAS that encapsulates its own clear-cut responsibilities, regardless of the agents. Hence the environment can play different roles in Multi-Agent Systems. It serves as a container and means provider for communication embracing interaction protocols. Regarding the social aspects of MAS, environment is seen, both as an organizational layer and, generalizing as a social behaviour infrastructure. Thus the environment can act as facilitator and/or as regulator. Oliveira in [Oli12a] adds another level of capabilities, further than, mediation and active monitoring, reinforcing the social dimension of the environment by introducing social intervention abilities. This social environment according to Oliveira's view can reason at a higher level, thinking about agents' collective behaviour and decide how to influence them.

2.4.4 Multi-Agent Systems

Putting together the concepts previously presented, MAS refer to a computer research domain that addresses systems that are composed of micro level entities -agents-, which have an autonomous and proactive behaviour and interact through an environment, thus producing the overall system behaviour which is observed at the macro level. Within the system, agents interact one with others pursuing to accomplish a set of goals. The goals can be consider either in individual or collective level [Les99]. MAS may contain multiple agents building up a *population*, or *society*. These systems are characterized by the lack of global system control where each agent has limited and different capacity of perception and acting upon the environment. That is, each agent has a distinct circle of influence being it just able to influence certain parts of the environment [Jen00]. Eventually, these circles of influence may overlap depending on the agent's relationship and from this social behaviours may arise. As such, agents negotiate coordination due to the capacity to act upon overlapped circles, or compete for a resource that might be important for achieving their goals.

Stone and Veloso in [SV00] provide a thorough description of the field of MAS. Authors present a survey of MAS literature discussing a taxonomy based on the degree of heterogeneity and degree of communication in the design of MAS. A particular characteristic of some agent-based system is related to the openness of the system. As open MAS, are characterized these organizations where the actual agents that will populate the system are

not known at design time and where agents may leave and join the system at any time.

2.5 Multi-Agent System for Incentive-Based Mechanisms and Policy Evaluation

2.5.1 Agent-Based Simulation and the Policy-Making Process

Policy-making (and forecasting the effects of it) is an extremely complex problem. It implicates the interactions among many diverse autonomous entities (expressed in different levels of abstraction) such as individuals, households, businesses and government organizations, as well as the physical world (environment). Each of these entities comprises interdependent economic, environmental, political and social behaviours. Since autonomous entities (expressed in different levels of abstraction) produce the effects of regulatory policy, the multi-agent approach to explain expectations about the effects of alternative policies, makes obvious sense. Agent-based models provide a powerful and scalable approach to analysing vital aspects of policy design and forecasting that traditional econometric models cannot as suggested in [BVES11, SWL+15, E+18]. The role of these models within the decision-making process is to evaluate the probable reactions of the system to policy mechanisms under both behavioural and structural aspects.

Policies are conceived in a way to drive individuals to change their behaviour. However, the way people adapt their behaviour might not be the one intended by the policy. People interpret the policies (as the social norms) in the context of their own state, according to their own idiosyncrasy and influenced by their social surrounding. Modelling the effects of introducing a new public policy is a very important issue. Thus agents being autonomous software entities that perceive and act in their environment can be used to model individual behaviour. Agent-based simulation models have been proposed in different phase of a policy definition and implementation. Dos Santos and da Rocha in [dSdRC12] introduce the concepts of agent-based model of public policy process and of policy artefacts. The former emphasizes the need of direct modelling and simulation of the main policy actors in terms of cognitive agents and their interactions, while the latter abstracts public policies that are addressed to the agents representing the authorities and other member of the society.

The benefit of agent-based motivation models in the policy-making and implementation processes is discussed in [PS11]. Authors demonstrate that the agent-oriented software engineering models are easier to read than process descriptions and focus better on relevant aspects. They show that agent-oriented models are suitable for modeling the social domain because they represent the goals and motivations of roles and individuals, and the notion of quality goals can be used to discuss high-level outcomes relevant for policy making. Wyner et al. in [WWBCA12, PS11] discuss the use of agent-based argumentation techniques taken from to provide intelligent support for intelligent support for opinion gathering and eliciting a structured critique of the policy-making process. Dignum et al. in [DDJ08] argue about the necessity to combine micro and macro-level models to simulation-based support for policy-making. Authors propose a complex model for agent reasoning that can describe the influence of policies or comparable external influences on the behavior of agents. In

this way simulation can support differentiation of behaviours in multi-cultural societies and guide the policy makers in their decision. Botti et al. in [BGGN11] present a MAS-based simulator to assist policy makers in the water-right market domain. The purpose of the development it is not only to assess normative regulations, but also elaborate more expressive performance measures to evaluate social issues in the market behaviour in order to evaluate values such as trust, reputation, and users' satisfaction. This type of measure will unfold new elements that will support decision-making about new policies. Jordan et al. in [JBE10, JBE12] introduce an ABM framework that it can be used to give insights into the dynamics of the housing market in relation to urban regeneration policies. Antunes et al. [ABC07] explored the tax compliance problem using agent-based social simulation. Following the e*plore methodology authors defined a number of agent models that reflect some characteristics both in individual and societal level to explore the micro-macro mutual influence of the simulation outcomes. Thus, they consider expanded history, individuality, adaptability, sociability, imitation, and social heterogeneity among the features to obtain a better realistic performance than the one of classical models based on probabilities and utilities.

With transportation being a backbone of modern economy, effects of road pricing on economic activity and its interaction with other economic and behavioural processes within urban areas must be considered. Traditional, analytical models are stretched to their limits trying to account for all effects and processes involved and interwoven with road pricing design and implementation. New solution concepts for this problem can be provided by combination of microscopic network simulation models with highly disaggregated information on travel demand, travel behaviour, activity locations and land-use. The design and the optimization of pricing policy in the transportation domain is a complex task as numbers of indirect effects need to be accounted in the application of the policies. For example, in the context of road pricing schemes Fosgerau and Van Dender consider in [FVD13] that congestion charging should not be account in isolation as there are important implications from traffic dynamics and the endogenous trip timing, from the heterogeneity of travelers and from the presence of travel time variability among others. Yet, design of pricing schemes needs cohesive assessment, considering the interactions between congestion and traffic network dynamics with heterogeneous behavioral as well as social, spatial, and economic factors.

To this effect, Zhang et al. in [ZLZ08] use agent-based techniques to explore the welfare consequences of product differentiation on congested networks and demonstrated the crucial role of user heterogeneity. Tsekeris and Voß in [TV09] underline the potential of agent-based models, due to its bottom-up approach with significant degree of disaggregation, intelligence, autonomy and ability to capture interactions among individuals. Nagel et al. present the MATSim
footnotewww.matsim.org traffic simulator to show, how multi-agent simulations approach with full daily plan for each agent can be applied for economic policy evaluation on a large-scale scenarios [NGB$^+$08]. A number of papers [GKN09, GKN10, KN12, BRHCR19] expand Nagel's approach, where it is discussed the econometric evaluation of different transportation policies using the multi-agent paradigm. In MATSim, each traveler of the real system is modeled as an individual agent. The simulator integrates activity-based demand generation with dynamic traffic assignment. The traffic dynamics are simulated using a macroscopic resolution of the transportation system. Activity-based demand generation (ABDG) models generate daily activities in sequence and trips connecting these

activities for every "agent" in the network. Demand generation thus is embedded in a concept of daily activity demand from which the need for transport is derived. Random utility theory is used to generate plans of daily activities. The approach consists of an iterative loop of:

1. Plans generation: All agents independently generate daily travel-activity plans

2. Traffic flow simulation: All selected plans are simultaneously executed in the simulation of the physical system.

3. Scoring: All executed plans are scored by an utility function

4. Learning: At the beginning of iteration some agents obtain new plans by modifying copies of existing plans.

MATSim model has been widely applied for transport and land-use studies, as it is the only model so far that consider economic activities and their interaction with other behavioral processes. Indeed several authors that studies public policy in the transportation domain have adopted it. Zheng et al. in [ZWAG12] combine a macroscopic modeling of traffic congestion in urban networks with MATSim in order to study and optimize cordon pricing schemes. Chakirov [CE12] discusses the challenges and drawbacks are considered in designing and evaluating economic instruments for influencing and changing people's behavior, with agent-based simulations. Amongst their findings, authors underline the importance of the heterogeneity among economic agents and thus diverse responses in providing incentives accordingly to different travel times, and the trip-timing factor and its role in the emergence of congestion phenomena.

Albeit, multi-agent system paradigm has been suggested as a complementary approach in evaluation studies of different policy approaches and during different phases of the their formulation, in transportation domain and particularly within the ITS area, the instantiation of agents has been kept only to study the consequences of a certain interaction between a given central authority and the agents situated in the traffic domain. Incentive-based policies that regulate the interaction among agents situated in the same (hierarchical) level haven't found similar treatment. The latter however, is being object of study in the area of multi-agent system as the essence of them. The question that arises thus is spontaneous. How can traffic and transportation domain the way are expressed in ITS can get inspired from the way MAS community applies the concept of incentives in other application domain built up by "selfish" entities?

2.5.2 Multi-Agent System and Incentives

Abstracting to higher level, socio-technical systems as ITSs are perfectly reflecting the openness and "selfishness" exposed in the open multi-agent systems; an unknown population of heterogeneous commuters populates it and pursuing their own goals and can join or exit the system; there is no direct control on their behavior. Following this reasoning MAS community has found affinities into the way micro-economic theories, such as pricing and direct reciprocity, trying to cope with systems where the "administrator" tries to convince self-

interested entities to cooperate converging towards the system's goal [MJS+19, ZSL+18]. These approaches and theories have been successfully applied in domain such as multi-sensor P2P, and other types of communication networks (either machine-to-machine or social). All these application domains share similar problems with the ITS area as they are "populated" by autonomous entities that try to maximize an internal utility function [RRG12, PVDS10, VO12a, VO08].

In designing these kinds of MASs it is necessary that a protocol that rules the interactions in the system is defined. Then given, protocol, the designer defines each agent's strategy. Sometimes, it is possible to impose both protocol and strategy to each agent. Under these conditions the agents can cooperate to reach a system acceptable solution. However, in open (distributed and large) socio-technical systems, as the aforementioned are, each agent represent a different stakeholder that has conflicting goals with the other (and eventually the system) and seeks to maximize its profit. Thus problems like resource allocation, coordination of actions and cooperation are common issues to be addressed and they are those issues that affect the transportation domain, seeing it as a, system. In this case resources are the road-segments that daily are requested for use by thousands of users. Traffic congestion takes place when the network overcomes its capacity in some points of it as a result of non-coordination and non-cooperation among commuters and between commuters and control authorities. A designer might be able to impose each agent's protocol and strategy; the agents can cooperate to find a good system-wide solution. But in open systems this is not feasible due to the aforementioned reason. So, the best a designer can achieve is a non-cooperative strategic analysis, in which the designer can impose only the protocol and can't control which strategies the agents adopt [DJP03]. Economists have studied analogous design problems within the context of auctions and mechanism design [Mas08, Var95]. In a mechanism design problem, the task of the designer is to choose the protocol (interaction rules) that provides agents incentives to act (and interact) in a way that met the designer's objectives.

2.5.3 Multi-Agent System and Mechanism Design

In contrast with the general equilibrium theory where agents respond solely to summary signals (such as prices for different outcomes) about the multi-agent problem, we assume agents act in a game-theoretic way, thereby modeling the effect their actions will have on other agents' actions. This more sophisticated micro-model of the marketplace of interacting agents and has caused MAS designers to start looking at the mechanism design theory. Specifically, MD deals with how to design systems so that certain system-wide properties (for example, efficiency, stability, and fairness) emerge in equilibrium from the constituent components' interaction. MD is particularly appealing for designing MASs with self-interested agents because it provides methods for simplifying the strategic problems facing agents at design time. Indeed, enforcing a normative framework or giving a reputation and/ or trust rating that reflect the behaviour of an agent can certainly encourage agents to improve their interactions, but it doesn't always eliminate strategic behaviour. The reader can find extensively presentation and formulation of the MD theory in [NR01, SLB08].

The MD concepts and frameworks has been used extensively to implement incentive-compatible mechanism in various domain and applications that follow the MAS paradigm and where the cooperation/coordination among selfish entities is of crucial importance for the overall performance of the system. This approach motivates agents to disclose their private information. As usually happens in market mechanism design, designers aim to construct a mechanism that has individual rationality (IR) and incentive compatibility (IC) properties. The former means agents do not suffer any loss when they use the system, and the latter means revealing truthful information is in their best interest. In algorithmic mechanism design, besides the IR and IC properties, designers also concern about computational complexity when computing an allocation rule and a payment rule for intended outcomes. The key technical difficulties lie in the combinatorial nature of the allocation rule and the interweaving relationship of allocation rules and payment rules. Examples of application it can be found in various domains and applications such as resource allocation and planning [BF19], collaboration in crowdsourcing applications [MOO18], pricing schemes [SDS21, BL19, MJS$^+$19], among others. Common characteristic of all of these works is the implementation of an incentive-compatible Vickrey-Clarke-Groves-based auction scheme. Thus typically in peer-to-peer/sensor network settings the mechanism will try to promote a truthful report of the local resources and compute socially efficient solutions.

As several authors in MAS community have argued, MD in its application necessitates of some assumptions that may not be verified in a (typical) open MAS setting [DJP03]:

- Agent's do not have unbounded computational power to calculate their preferences for all the possible outcomes and strategies (bounded rationality) a priori
- The mechanism infrastructure in a centralized mechanism might not be able to compute the outcome because the problem is intractable.
- Most of real MASs are open and dynamic, while the classic MD considers static environments.

Additionally, Rehák et al [RPT05] note that also MD, have limited applicability due to possible polyvalence, strategic behavior and willingness to keep some of their knowledge private cannot be completely addressed by the current mechanisms. Larson et al. in [LS05] consider the case of deliberative agents participating into a MD. Such agents deliberately execute an information gathering process in order to determine their preferences. Agent's preferences determine what it will reveal to a mechanism and in the same way, what the agent plan to reveal influence the way it selects to order its preferences. Authors have proposed a set of proprieties a MD should exhibit in the case of deliberative agents; preference formation-independent, deliberation-proof, non-misleading. Authors conclude that it is impossible to obtain all three properties together.

Some application of MD have been proposed also in the transportation domain as the main focus of the community is the reduction of traffic congestion (and thus cost related to it) by application of pricing mechanisms [BHF12]. In their work, the most relevant application of MD in transportation and traffic routing is discussed a pricing mechanism that wants to take into consideration both preferences and fairness among individuals. When a new passenger arrives at an origin node, he receives information from the authority on the current network condition. The authority either suggests using public transportation if

the network is about to be congested or provides him with the minimum travel time required to complete his trip. In the latter case, the passenger then reports his maximum tolerated travel time that is not less than the minimum travel time announced by the authority. Based on the current traffic condition in the network, the mechanism then offers the passenger a path to his destination that matches with his preference. According the authors the mechanism bears the incentive-compatible property of the mechanism and its computational feasibility. The papers contemplate only a simple network with a couple of origin-destination pairs and the passengers don't join the system.

Tu et al. in [TZL+22] provide a comprehensive review for the economic and game theoretic approaches proposed in the literature for incentive mechanism design. Their taxonomy of the economic and game models is provided in Figure 2.2.

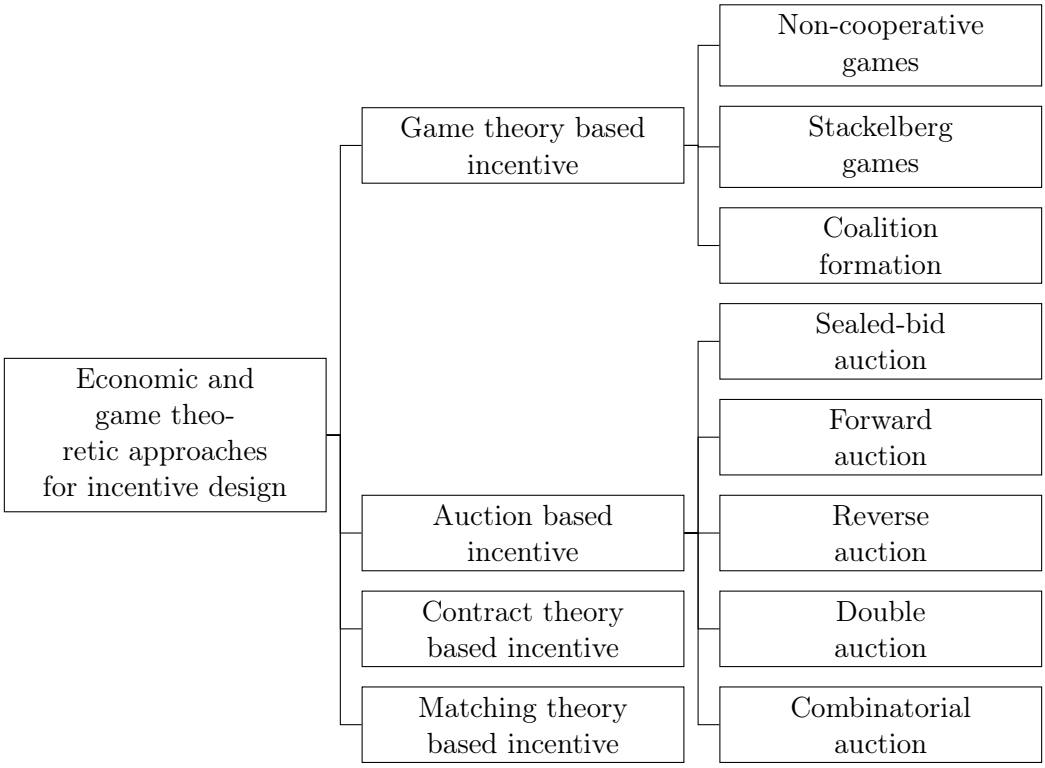


Figure 2.2: A taxonomy of economic and game approaches for incentive mechanism design (adapted from [TZL+22])

Game theory can represent the multi-participant interactive decision-making dilemma in which a participant's decision may impact the actions of other participants. [TZL+22] distinguishes three classes of game theory frameworks for incentive mechanism design:

- *Non-cooperative Game*, where each player is considered to be selfish which only cares about the maximization of its own payoff rather than the social welfare of the system. In such games, there is not cooperation or agreements among players.

- *Stackelberg Game*, a sequential-move game in which the players acting as the leaders move first and then other players acting as followers move after observing leaders' moves. The game aims to model multi-agent decision making processes and maximize the utility of both the leader and the followers given the leader's strategy.

- *Coalition Game*, a cooperative game with the aim of maximizing a common objective of the coalition. Moreover, enforceable contracts are made among the players. In this case, the players can coordinate strategies and reach an agreement on how to assign the total payoff to the players in a coalition. The objective of a coalition game is to find a stable solution which ensures that the outcome of the game is immune to changes of groups of players (i.e., each player has no incentive to move from its current coalition to another coalition).

On the other hand, an auction is an economic mechanism whose aims are to allocate goods and create associated prices through a bidding procedure. Among the auction types commonly applied to incentive mechanism design are:

- *Sealed-bid Auctions* are biding procedure where the buyers submit sealed bids simultaneously to the auctioneer. As a result, no bidder can see the bidding information of others and cannot adjust its own bid. There are three types of sealed-bid auctions:
  - *First-price sealed-bid auction*: The bidder with the highest bid is the winner who can receive the item and pays the highest bid;
  - *Second-price sealed-bid auction*, also known as Vickrey auction, the winner only pays the second highest bid rather than the highest bid that it submitted. The desirable characteristic of the Vickrey rule is that achieves truthfulness, because winner pays the price less than its expected price. This aspect enables Vickrey auction to be widely used for the implementation of incentive mechanism design;
  - *Vickrey-Clarke-Groves (VCG) auction* is a multi-commodity Vickrey auction. The procedure assigns the commodities a socially optimum way, and the winner pays for the loss of the social value for obtaining the assets. The rule incentive bidders to reveal their true value for the commodities;
- *Forward Auction*, where multiple buyers submit their bids to compete for the requested items offered by one seller;
- *Reverse Auction*, where multiple sellers submit their asking price, to compete for selling the items to a single buyer;
- *Double Auction*, where it is necessary to match the supply and demand in markets with multiple sellers and buyers (i.e. electricity markets). In a double auction, buyers and sellers simultaneously submit their bidding and asking prices, to an auctioneer. The auctioneer determines the so-called clearing price of the market;
- *Combinatorial Auction*, where each bid of a buyer indicates a bundle of multiple commodities rather than an individual commodity. Based on the information included in the bid as well as the capacity of commodities from sellers, the auctioneer determines the optimal allocation strategy as well as the winner of the auction (i.e. winner determination problem).

Finally, two other traditional approaches for incentive mechanism design stemming from economic theories are the *Contract theory* [BD04] and *Matching theory* [EE17]. These to theories have been regarded as two powerful tools to model the dynamic and mutually beneficial relations among different types of rational and selfish agents.

2.5.4 Beyond Mechanism Design as Incentive Schemes

Zhang and Parkes in a series of papers between 2008-2009 coined the concepts of the value-based policy teaching and environment design [ZP08, ZCP09, ZPC09]. The concepts follow the incentive-based schemes where an interested party's utility (system social welfare) depends on the actions of a (single) agent. The policy teaching reflects the way of providing limited incentives to induce an agent policy that maximizes the total expected value of the interested party. Authors consider a setting in which the agent performs a sequence of observable actions, repeatedly and relatively frequently. The interested party has measurements of the agent's behavior over time, and can perform limited changes in the environment by associating additional rewards with world states or agent actions. The agent may choose to behave differently in the modified environment, but the interested party cannot otherwise impose actions upon the agent. Environment design permits us to study settings where the interested party cannot design the agent but is still interested in its decisions [ZCP09]. By making small changes to the environment, the interested party aims to align the agent's decisions under the modified environment with the decisions desired by the interested party. The latter reflects, on our opinion, the dimension the environment tend to enable according Weyns in [WOO07] and Oliveira in [Oli12b]. As the agent's local rewards (and thus its preferences and utility function) may be unknown to the system designer, Zhang and Parkes consider an indirect preference elicitation approach (inverse reinforcement learning) inferred from observing agents over repeated interactions to obtain desired actions from the agents.

Dufton and Larson in [DL09]extend the framework by Zhang and Parkes, considering a multi-agent setting where all agents are in a shared environment so that any changes introduced by the interested party are experienced by all agents. However, in large open systems not all the agents will follow the suggested policy (the desired actions). So, in their proposal author suggest two ways of overcoming the issue. First, the designer (interested party) tries to detect the largest subset of agents interested to receive the "target" policy with a single incentive scheme. Alternatively, it searches to find a range of values (rewards) to allow for deviations from the target policy.

Centeno et al in [CB11c, CB11a, CB11b, CBH13] inspired by the works of Zhang and Parkes, Dufton and Larson, consider a distributed incentive mechanism deployed by means of a network of institutional agents, called incentivators. The incentive mechanism is able; to learn which actions each agent should perform populating an open MAS from the global system point of view, and to learn how agents can be encouraged to perform the desired actions. Authors consider a peer-to-peer file sharing application where each agent (peer) in the system is assigned an incentivator (interested party). The objective of the incentivator is to learn (following a q-learning approach) and apply an incentive policy based on its agent preferences. Also in this case the incentives are given through modification of the environment following the paradigm of environment design. The incentivator applies the rewards based on its local perception of the environment about the performance (global

utility) of the system. To reinforce the estimation of the system utility, authors use for each incentivator a gossip-based aggregation algorithm to account for the estimation of the other incentivators in the mechanism.

We can notice some similarities between the proposals in [DL09, ZP08, CBH13, FBM20] as the incentives provided by the interested party are expressed through modifications in the environment. In all the cases the interested party follows a "policy-teaching" approach where an entity, working on behalf of the system, encourages an agent to adopt some desirable behavior. This is obtained by modifying the dynamics of the environment. However in the scaling of the approach is different; in the case of Zhang and Parkes we have one-to-one (interested party to agent ratio) correspondence, while in the case of Dufton and Larson we note a one-to-n. Centeno et al. propose a distributed network infrastructure for the interested party with one-to-one correspondence.

This kind of incentive-based "adapting" approach, where reward policies are not constants but change according the underlying dynamics it is followed in Hermoso et al. in [HCF15] by introducing the concept of incentive schedules. A different perspective of incentives offers the proposal from del Val et al. [DVRB12]. Authors consider the case of decentralized service discovery in Service-Oriented MAS where the cooperation/collaboration is not always granted with negative repercussion to the system performance. They proposed a composed scheme of incentives (an increase to the agent's utility function) and structural mechanism (inherent of the network) such as social plasticity (strength of bonds among neighbors) to stimulate the emergence of cooperation. Zhang et Van de Schaar [ZVdS12] use reputation as incentive in interaction protocols for crowdsourcing application. Their results show a maximization of the social welfare as they prevent the "free-riding" problem of workers and incentivize them to contribute their efforts in the task-solving processes. Kastidou [KC09] discusses trust and reputation as incentive to promote truthfulness in on-line communities. Pippin and Christensen in [PC12] present an approach for using observation based trust and a shared reputation mechanism in determining which agents to include in multi-agent auctions. The present work-plan proposal lays in the intersection of MAS, agent-based simulation and intelligent transportation system. We are interesting into the application and evaluation of incentive policies for social aware mobility systems. Thus is licit to ask how agent technology has so far dealt with this issue and how the literature in agent-based incentive mechanisms can inspire their application in the transportation domain?

We have seen how the game-theoretic and economic theories incorporated in the MD have been proposed to allocate resource in the transportation domain. Here as resource we can consider both the roads composing the network and the costs (both time and monetary) drivers are willing to pay. In that sense multi-agent learning algorithms have been proposed as a natural approach (because of the miming human behavior) to addressing congestion problems in traffic and transportation domains [DKLS18, RRNT20]. Congestion problems are described by having the system performance depend on the number of agents (drivers) that select a particular action (a route, a lane), rather on the intrinsic value of those actions. Tumer and colleagues [TP13] propose a method based on timelines to align social welfare and agent preferences to improve congestion. The method is twofold as it includes both the perspective of the city manager and the drivers' side. Even though we cannot consider the proposal as operative one however can offer a good starting point to model the two entities (city manager and drivers) to a more robust and deployable approach. In a different

approach, Bazzan in [Baz19], discusses the computation of optimal social welfare alignment with the agent choices by means of a combination of meta-heuristics and reinforcement learning. Here, the city manager computes traffic assignment that converge to the optimal system operation by, periodically, encompassing in the solution direct observations from the single agents in the environment. From the other hand agents incorporate part of the solution produced by the meta-heuristic to their knowledge and accelerate in this way their learning process.

An important advancement in the ITS domain is within the mobile communication field with the introduction of the vehicular ad-hoc networks (VANETs) that enable the exchange of information among vehicles and between vehicles and infrastructure (V2V, V2I). This fact combined with the advent of the autonomous vehicle concept give rise to the so-called cooperative mobility ITS solution. However, this new technology and agent-based applications may lead to the emergence of self-interested systems (e.g. car owners) that will care more about their own welfare than the social welfare of their peers. Following this rationale Lin et al. in [LKS07] investigated the benefits achieved by self- interested agents in vehicular networks and whether mechanisms can help gossip agents overcome malicious agents in transportation networks. They concluded that this kind of "malicious" behaviour has limited effect, differently to what happen in other domains. Nevertheless, further experimentation is necessary where different types of behaviours are modeled.

Vehicular networks still share some common features with other mobile ad-hoc networks where collaboration among nodes is desirable to assure system performance. Vehicular networks are self-organizing and are formed directly by a set of smart vehicles. To achieve the network's designed operational levels individual vehicles need to cooperate in packet forwarding in vehicle-to-vehicle communication. However, some selfish users in the vehicles may not want to forward the packets if it will not benefit them in some way. This is a typical situation encountered in MANET and other multi-sensor networks where nodes need to be motivated to cooperate. In this case a paradigm shift of applying incentive-based schemes from one application domain to another can be performed. An extensive review of the proposed in the literature approach for this particular application is out of the focus of this proposal, as we don't have interest in discussing the communication layer interaction protocol. In any case we consider a fully working communication channel among the vehicles and the network infrastructure. Eventually what could be subject of research is the semantic part of the communication related with cooperation (and thus coordination) issues at the mobility level.

2.6 Summary

Along this section we have reviewed some fundamental concept interlaced in this the. We have started by considering the transportation domain and in particular way the Intelligent Transportation system area. We show the use of agent-based technology considering its dual nature both as programming and modeling paradigm, that is, using MASs to design an incentive or policy and using MASs as modeling metaphor to represent o society where the introduction of an incentive or of a policy needs to be assessed before the actual deployment on a given system.

We have introduce the "problem" of (public) policy making and show through the literature review how and why agents can provide support in the decision-making throughout all the stages of the policy definition. Our focus in the present proposal is how to devise and evaluate incentive-based policies. Thus we introduce briefly the incentive theory as it is defined in the economics domain. We present how policy-making and incentives are seen in the transportation domain and how agent-based modelling and simulation has been used to as evaluation tool. Finally we considered the way MAS community has employed the incentive-based mechanisms in various domain of application and how the ITS can adopt and extend the MAS-based approaches.

To summarize this chapter of the backgrounds and related work we would like to consider some aspects that have been generated as result of the review. The first is the necessity for a conceptual framework of a dynamic and competitive resource-based environment where solutions and schemes can be tested thoroughly. However, such an approach only partially would reflect the aspects characterizing such environment as it would required different modeling representations, from microscopic to macroscopic, where interaction among entities composing the system and the infrastructure of the environment need to be accounted for. Only this way decision-makers can witness the emerging phenomena of coordination/cooperation among the agents and the infrastructure.

Second, cooperative mobility systems is the next revolution in the ITS area. In this context, MAS-based theory and application definitely can have an important role in the definition and implementation of such systems. As we have seen incentives mechanism have been proposed to corroborate cooperation mechanism in open systems composed by selfish entities. The latter comes to provide and added value in justifying the research line of MAS-based design and evaluation of incentives and policies in competitive environments.

Chapter 3

A Conceptual Multi-Agent System Model for Resource-Based Integrated Markets in Dynamic and Competitive Environments

3.1 Introduction

Markets are economic systems where two or more parties engage in resource exchange, whether related to goods or services or any other trade-able items, such as labour or rights. Their main role is to coordinate the flow of a given demand in respect to a given supply of resources. Due to their adaptability, different market structures and regulation policies emerge to better serve specific domain's applications. One of the markets' characteristic, as societal structures, is their evolution and adaptation to new rules and organizational complexities. In this sense, different market types and regulation policies emerge to better serve specific domain's applications. The visibility of a market organization and its stratification varies from one application domain to another. For example, we have the case of the power grid distribution network where the physical system is explicitly associated to a number of markets: a wholesale and retail instances with their own mechanisms and type of participants (gencos, providers, consumers) [SKRS13b, SKRS13a]. From the other hand, transportation systems exhibit an implicit opaque market operation (in this case are considered government agencies, service providers, and commuters as participants). However, both system consider market-based policies to control an unbalanced demand, resources allocation, or market failures [PD11, SBM$^+$10b]. Contemporary information systems provide extended capabilities to support both system and market operation as well as improve the observability and controllability of the system. The proliferation of socio-technical systems and other technological paradigms has allowed market-oriented approaches to be implemented, achieving more efficient control on resource allocation and supply [RLSS10, RL11]. An additional functionality they have introduced is that they increase the awareness of consumers. While previously they were considered "passive" elements of the market with limited decision making, now they can act in more active way. This possibility has fostered the emergence of new "side-market" structures, operating in parallel with traditional markets within a given system. These new structures are characterised by: a) the possibility of consumers (typically resource users) to act as providers (or even producers), and b) their volatility. Examples of such economic structures can be considered the virtual power plants (VPPs) concept in smart grids [YTP09]. Other instances of such sharing economies can also be met in other domain applications with similar

characteristics (e.g.car-sharing [HG11], crowd-sourcing [FHI11], cloud computing [BYV08], etc.).

It is very important to understand how these different market structures interact and what are the impacts on the whole system. That is, market failures can emerge due to externalities, such as possible imbalances, self-interest demand, poor prediction on resource production, or failure in the production itself. What the more appropriate regulation policies should be applied? Moreover, the aforementioned integration becomes more important when decentralized and deregulated emerging markets are considered, such as peer-to-peer and virtual markets. A holistic view is still not well documented.

This chapter makes the following contributions:

1. We present the design and formalization of the Resource-based Market Agents Systems (ResMAS), a conceptual model of multi-markets environments. We discuss an overview of the potential market structures that can exist in contemporary systems, exemplified in a particular instance: the electricity market. Our objective is to define the elements that compose the system in a formal way and characterize their interactions.

2. We propose a distributed Demand-Side Management(DSM) for a Home Energy Management (HEM) system based on the MAS paradigm, in which agents are in control of specific appliances and schedule their operation by negotiating with a *resource* agent. For this purpose we use the ResMAS model for formalizing a market structure as an enabler for control and usage coordination of the shared resources in the HEM setting.

3. We present and discuss the results of a simulated HEM case study, to showcase that the proposed market model can contribute towards comfort and sustainability.

The rest of the chapter is organized as follows: Section 3.2 overviews market organization aspects and discusses the multi-agent market systems related work. Section 3.3 presents the ResMAS model, complemented by the definition of market processes in sub section 3.4. Section 3.5 discusses the formalization of a HEM as market structure, and present preliminary simulation results in subsection 3.5.3. Finally, Section 3.6 summarises the main topics of this chapter.

Earlier works of this chapters appear in [RKC+17, MRK21, MKR22].

3.2 Related Work

A market is any context or process in which two parties engage in trading services, physical assets, or financial assets. For the concept of market organization we consider the mechanisms and the participants involved in the trading of goods. Figure 3.1 depicts an idealization of a market ecosystem composed of five markets, each having its own organization:

Wholesale market (M.1). The principal actors that participate in this market are: the *suppliers* (E.1) and the *providers* (E.2). Considering the case of electricity market, suppliers are the producer companies that own power plants, while providers are the retail distributor utilities. Wholesale markets are characterised by the trade of big volumes, and by the pricing mechanisms (usually auction-based [Tes09]).These markets are built on the aggregate demand and supply curves and their crossing point lead to the cleared quantity and the cleared price for each time step of the next day. Depending on the domain, consider we might find different wholesale markets operating in parallel.

Retail market (M.2) is composed of a group of providers and a group of *customers* (E.3). Characteristics of the market are: a) the low volumes of products traded between a provider and the end-user (customer), and b) the tariff mechanism with which the price of the goods is set. Providers design and publish tariffs in order to respond to an aggregate demand (customers' portfolio) in a way that will allow to maximize their profits and match the supply they purchase in the wholesale market [GKB+11, BJWA13].

Bilateral contracts market (M.5) are characterized by the establishment of bilateral financial or physical relations between suppliers, on one side, and eligible customers or providers on the other [NBZ05]. These contracts involve separated negotiations for several aspects, such as the price and a large volume of goods/services to be supplied and consumed over a specified period of time, in order to satisfy a demand not applicable on the other markets.

Virtual markets (M.3) are emerging organizations and can receive different interpretations based on the application domain that is considered, differently from wholesale, retail and bilateral market organizations, which reflect the traditional trading contexts. Characterized by a dynamic aggregate demand that forms short-term coalitions of customers to achieve a particular goal, virtual markets can operate similarly to a retail market. However, a representative acts as a buyer on the other markets, while switching role as provider for the others in the coalition. Examples of such economic structures are the virtual power plants (VPPs) concept in smart grids [YTP09, KK15].

Peer-to-peer Markets (M.4) are organizations where customers can exchange resources (goods or services) between themselves, without the existence of a provider. It is a market that emerges within the context of *sharing economy*, where participants grant collaborative access to products or services [Hei13]. Peer-to-peer markets are often characterized by high degree of heterogeneity [EFL16].

Market Regulation (represented by the "R" in Figure 3.1) is twofold: one with a systemic scope and the other with agent-scope. The first is usually referred to as governmental regulation and in real-life is provided by regulation agencies. It comprises the norms established in order to guarantee the correct operation of the system. On the other side, agent-scoped regulation comprises the mechanisms participating agents (usually providers) provide to some groups of customers in order to influence their behaviour, such as incentives or discounts. If some compliance rate is achieved, the provider benefits from this policy by manifesting more competitive participation.

Usually, managers use economic tools such as market-based policies to guide their decisions and drive their system towards the desired outcome. In [RGN+20] authors highlight the

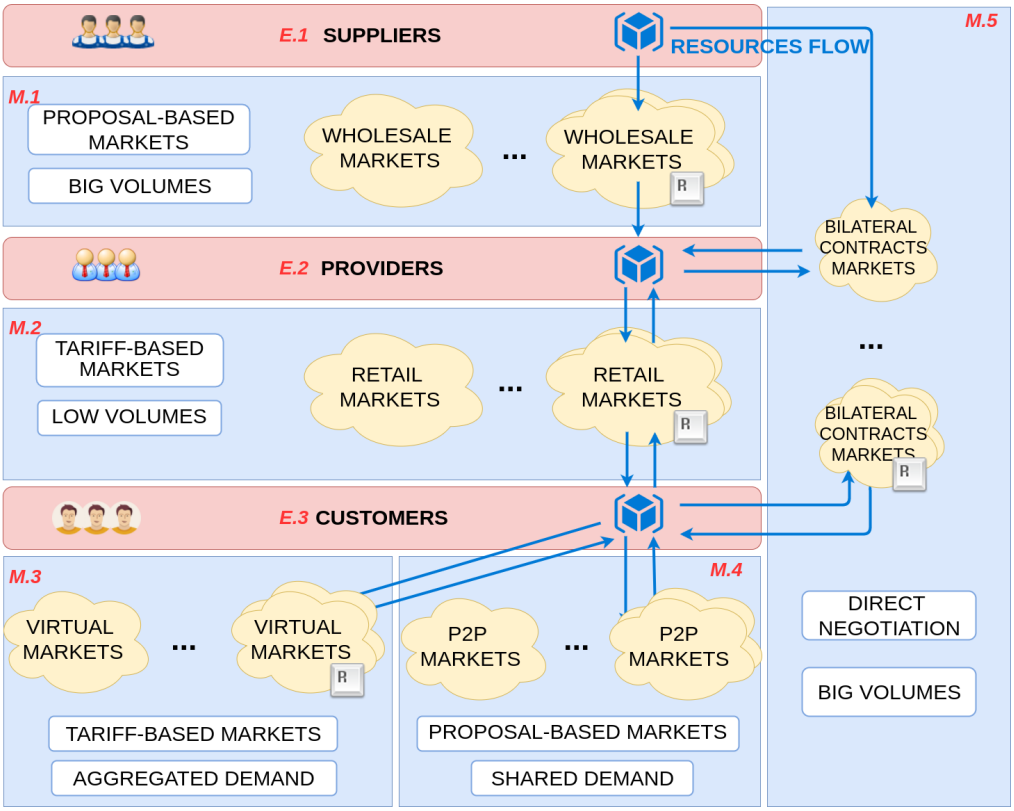


Figure 3.1: An integrated architecture for multi-market MAS

importance of taking into account the consumers' behaviour in planning an efficient pricing strategy in order to reduce workload at specific peak hours. Yet, current decisions focus on a single market in order to apply a regulatory policy, which often leads to a short-sighted decision in such integrated markets environment where policies might have impact on the whole system.

Thus, the ResMAS environment described below is put forward as a first step towards this complex scenario of multi-market applications, where regulation plays a central role regarding policy-making processes.

3.3 A Conceptual Architecture for Market-Based Multi-Agent System

Given the growing relevance of market-based environments in different scenarios, novel approaches including autonomous and automatic decision-taking systems will be needed. In this sense, Multi-Agent Systems are presented as the right direction towards representing human preferences and decisions. In the following paragraphs we describe a conceptual architecture that comes to fill the gaps between the broad spectrum of market-based applications and impacts of individual decisions in the whole system.

Our general purpose architecture can help researchers to instantiate simulation and deployment of new applications where markets are a fundamental piece for the ancillary services and operations. Moreover, we intend to use this conceptual architecture as a test-bed framework for creating new regulation mechanisms. In fact, market-based regulation provides two possible layers of regulation: one with a systemic scope and the other with provider-scope. The first is usually referred to as governmental regulation and in real-life is provided by regulation agencies. It comprises the norms established in order to guarantee the correct operation of the system. On the other side, provider-scoped regulation comprises the efforts taken by some agents in order to keep a competitive participation: by creating a self-sufficient network, providing a peer-to-peer mechanism for bilateral negotiations, etc. Thus, the ResMAS environment described below is put forward as a first step towards this complex scenario of multi-market applications, where regulation plays a central role. We assume a discrete-time approach, so $T = \{t_1, ...t_n\}$, and following the description of the conceptual architecture provide a simple simulation model using ResMAS.

3.3.1 ResMAS

Resources are common elements in market-based systems, appearing under different names and kinds. Agents play the market game in order to exchange resources and fulfill their needs for required resources while providing their own available resources. In this context, the requiring agent is called *buyer* and the providing is called *seller*. Resources can describe physical or virtual goods, services or information. We define ResMAS (Resource-based Market Agent System) as an environment with a set of resources Res, markets $\mathcal{M}$ and agents $\mathcal{A}$.

$$ResMAS = \langle Res, \mathcal{M}, \mathcal{A} \rangle$$

3.3.2 Resources

In the ResMAS world, there can be a limited or unlimited quantity of resources, given their nature (type). We define a resource as follows.

Definition 1 (Resource)**.** *A* resource *comprehends two main concepts: the resource type τ, defined in an ontology, representing its name (or nature); and the information about its application domain σ. The domain σ is the dimension where the resource is located and can be seen as the applicable unit. $r = \langle \tau, \sigma \rangle$. In practice, agents deal with resource instances, which are samples of that resource, defined in the domain expressed by r.*

For instance, let r_{elec} be a resource instance of electricity: $r_{elec} = \langle \text{SOLAR\_ENERGY}, 50 \text{ Kw} \rangle$ means that r_{elec} is 50 Kw of solar energy, an instance of the resource electricity. Two basic operations are provided for managing resource instances: $addition(r_1, r_2)$ and $subtraction(r_1, r_2)$. These operations are valid only for resources of the same type: the result is a new resource instance. Thus, different resource instances can be aggregated in a set $Res = \{r_1, ..., r_q\}$ representing a collection of resources. Here, two basic operations are provided: $add(r, Res)$ and $subtract(r, Res)$. The first allows adding new resources to the set and the second allows removing resources from the set. Agents use these operations

in order to manage and exchange resources in the markets.

3.3.3 Markets

Definition 2 (Markets)**.** *Different markets can be found in a single ResMAS system:* $\mathcal{M} = \{m_1, ..., m_k\}$*. They comprise the negotiation environment where agents can exchange resources. Each market* m_i *have a group of allowed participants* $Part \subseteq \mathcal{A}$*, a set of artefacts* Art*, a regulation mechanism* Reg *and, finally, a set of processes* $Proc$ *that describe resource allocation mechanisms.*

$$m_i = \langle Part, Art, Reg, Proc \rangle \tag{3.1}$$

The *participants* $Part$ represent the set of agents that are allowed to participate in the market. It means that different markets can filter which agents can participate. *Artefacts* are market objects that carry information over the negotiated resources: $Art \subseteq \{tariff, proposal, transaction, contract\}$.

A *tariff* can be seen as a plan with multiple associations between quantities (or specific resource instances) and the price to pay for each of them, called rates, and a set of fees (sign-up fee, periodic fee, withdraw-fee, etc.), so $tariff^{\tau} = \langle Rates, Fees \rangle$ with $Rates = \{\langle r, price \rangle, \dots\}$ where $price \in Res$ is the price to pay for the resource r. In a tariff-based process, the tariffs are published in the market and the customers can subscribe to that plan. Actually, tariffs act as templates for the contract applicable rules. On the other hand, a *proposal* is an exchange proposition between two individuals. Differently from tariffs, there is no subscription plan here, just a direct negotiation for a resource instance. $prop^r = \langle price, a_i, a_j \rangle$, where r is the resource, the desired price $price \in Res$, and the seller agent $a_i \in Part$, and the buyer agent $a_j \in Part$.

Tariffs and proposals are subject to a *contract*, which contains the rules of the deal and determines the services and the obligations the agents shall comply in order to assure the agreement. $Contract = \langle Parties, Service, Obligations \rangle$. Finally, a *transaction* represents the resource exchange between the agents, from the agent a_i to the agent a_j, following the corresponding payment. Multiples transactions might occur under a contract.

Still in the market elements, the *regulation policies* Reg represent the mechanisms used to provide control over the system and reduce negative externalities such as market failures. In this chapter, we consider regulation policies as simple authorizations, but we intend to explore this area in the future using more complex mechanisms, such as incentives, norms and trust. Section 3.4 is fully dedicated to better explain how market processes are conceptualized in ResMAS. Basically, we considered two types of market processes: tariff-based and proposal-based. Although one can design different processes, we believe that these two types can characterize most of the markets, even with different requirements in terms of the flows and agent activities, the basic operations are usually either tariff-based (pool) or proposal-based (direct). Note the distinction from the term *protocol* in the way that the processes are much more generic, describing the agents' responsibilities and activities in the whole allocation mechanism flow (that might include some negotiation protocols in the task to match buyers and sellers).

3.3.4 Agents

Definition 3 (Agent)**.** *The set of agents $\mathcal{A}$ is composed by the agents that participate in the ResMAS environment. A simple* agent *$a \in \mathcal{A}$ is an entity that has a role, which specifies its behaviours, two dynamic sets of resources , the available and the required ones and goals Γ.*

$$a = \langle role, Avail, Req, \Gamma \rangle, a \in P \tag{3.2}$$

So, let's call a' the agents that can manipulate the resources. In addition to the simple agent definition, customers and suppliers can have a group of appliances App that represent the actual devices that can use the resources and a Π set of preferences for using this appliances. Thus,

$$a' = \langle role, Avail, Req, \Gamma, Apps, \Pi \rangle, a' \in C \cup S \tag{3.3}$$

We will write $Avail_a^t(r)$ or $Req_a^t(r)$ to denote the available or required quantities of resources r that agent a has at the time t.

Definition 4 (Group)**.** *A* group *is an aggregation of agents that play the same role, which can be supplier, provider, customer. Three main groups can be defined: S, P, and C:*

$$S = \{a \in \mathcal{A} \mid role_a = supplier\}$$

$$P = \{a \in \mathcal{A} \mid role_a = provider\}$$

$$C = \{a \in \mathcal{A} \mid role_a = customer\}$$

Definition 5 (Appliances)**.** *For the sake of simplicity, we consider supplier agents as only capable of producing, never requiring resources ($Req = \varnothing$). Providers, in turn, do not produce or consume, just negotiate resources, acting as intermediary agents (brokers). On the other hand, customers can have both production and consumption capabilities. The set of appliances of an agent a, $Apps_a$ is defined:*

$$Apps_a = \{app_1^r, \ldots, app_z^r\}, \quad \textit{iff } a \in C$$

To represent the actual resources usage, a load function $\mathcal{L}$ is defined. Given a appliance app^r in an instant of time t (where $T = \{t_0, ...t_n\}$, is the time horizon), the load function $\mathcal{L}$ represents the instantaneous consumption/production.

$$\mathcal{L} : Apps \times T \to \mathbb{R}$$

Definition 6 (Appliances Preferences)**.** *An* utilization occurrence *of the appliance U_{app}^r is described by the appliance activation in a given time t with the duration δ. So $U_{app} = \langle t, \delta \rangle$.*

Each agent a has a set of possible utilizations for the appliance app^r that can be used to create an actual schedule. So, for each appliance, the agent has a totally ordered set π_{app} corresponding to the preferences of the agent a_i over the possible utilizations of the appliance: $\pi_{app} = \{U_1 \succeq U_2 \cdots \succeq U_w\}$. Given that the agent might have different appliances, the partially ordered set resulting from the union of all of an agent's preferences is $\Pi_{a_i} = \pi_{app_1} \cup \pi_{app_2} \cdots \cup \pi_{app_z}$.

Definition 7 (Scheduling mechanism)**.** *In order to use the appliances, the customer agent creates a schedule function to organize the activation of appliances. The* scheduling mechanism Ψ *corresponds to the actual plan of executing some of the utilization occurrences.*

Due to space limitations, the scheduler modelling is out of the scope of this work. We only refer to the scheduled tasks in order to know what are the actual appliances activated in a given time t. The results of the scheduler Ψ are represented as:

$$\Psi_a^t(app) = \begin{cases} 1, & \text{iff } app \text{ is activated in } t \\ 0, & \text{otherwise} \end{cases} \tag{3.4}$$

The *list of active appliances* at time t is $Lapp_a^t = \{app \in Apps \mid \Psi_a^t(app) = 1\}$

Definition 8 (Required resources)**.** *The* required resources $Req_a^t(r)$ *are the resources agent a will need in a given time t. In ResMAS,agents can negotiate resources through all the markets they are allowed to participate in order to acquire the required resources from other agents. As seen previously, suppliers present an empty required set. A provider's tariff subscription mechanism makes its required set an aggregation of its subscribed customers' required resources ($C\prime \subseteq C$). The resources amount required by a provider is called* demand *and represented by Dem. Thus, a customer's required resources comprise the sum of the load $\mathcal{L}$ of all appliances that are activated in the given time t.*

$$Req_a^t(r) = \begin{cases} 0, & \text{iff } a \in S \\ Dem_a^t(r) - Avail_a^t(r), & \text{iff } a \in P \\ \sum_{j=1}^{z}[\mathcal{L}(app_j, t) \cdot \Psi_a(app_j, t)], & \text{iff } (a \in C) \wedge (app \in Apps_a) \end{cases} \tag{3.5}$$

$$Dem_a^t(r) = \sum_{i=1}^{n} Req_{a_i}^t(r), \quad a_i \in C' \tag{3.6}$$

Definition 9 (Available resources)**.** *The* available resources $Avail_a^t(r)$ *are the resources the agent a can provide in market in a given time t. Similarly to required resources, agents' available resources are computed differently according to the agent group. Suppliers and Customers have different available resources in each time t. It means that either they have production capabilities, so $v \in \mathbb{R}^+$. or they do not and $v = 0$. Providers, in turn, depend on the subscriber's customers available resources. The available amount is called* Supply *and represented by Sup.*

$$Avail_a^t(r) = \begin{cases} v \in \mathbb{R}, & \text{iff } a \in S \cup C \\ Sup_a^t(r) & \text{iff } a \in P \end{cases} \tag{3.7}$$

$$Sup_a^t(r) = \sum_{i=1}^{n} Avail_{a_i}^t(r), \quad \text{iff } a_i \in C' \tag{3.8}$$

3.4 Modelling Market Protocols as Processes

In Section 3.3.3 we said that processes are an important element of markets. They represent the logical flow lead by the market operator in order to coordinate agent activities and allocate the resources by using a *negotiation protocol*. Negotiation protocols are sub-processes that try to find a match between possible buyers and sellers, according to specific rules. Examples of negotiation protocols are auctions, direct negotiation, etc. As a part of the process, we do not intend to further detail the negotiation protocols in this chapter. Instead we assume that even if the negotiation changes, it will not affect the essence of the process.

The process, in turn, seems to define the whole market. In our model, two processes are considered: tariff-based and proposal-based. Tariff-based processes, as seen in Figure 3.2, occur in two main flows. The tariff publication (left) starts with the intention of providing a tariff for a group of customers and if the market operator authorizes, the customers can see it in a tariff pool and possibly subscribe to it (right). Again, if the market operator authorizes this subscribe operation, a contract is established (a sub-process to be described later). The process ends when the contract is finished.

The tariff publication flow starts with a server that want to provide a service (or good) by assuming tariff-based contracts. In this case, the server specifies a tariff and send it to the market operator (responsible for the regulation/regularization) so it can be analyzed. The operator then, verifies whether the tariff is in accordance with the market rules. If the tariff is not authorized, the flow goes back to the server so it can review the tariff conditions. On the contrary the tariff is authorized, it goes to a public market pool, accessible by all the participating agents. All the agents are notified that a new tariff was published in the market.

On the other side, the tariff selection flow occurs in the client side. Two start events are possible, either when the client asks the market for tariffs, starting the process or by receiving a new tariff message from the market. In the first case, the client asks the tariffs and the market operator answers with the corresponding (published) tariffs. The client then can select a tariff. The process ends When no tariff is selected. On the other hand, if a tariff is selected, a subscription message is sent to the market operator, which evaluates whether a contract is authorized or not (repeating the process). In the positive case, a contract is consolidated in a sub-process, explained in Figure 3.4. The process ends When the contract is finished.

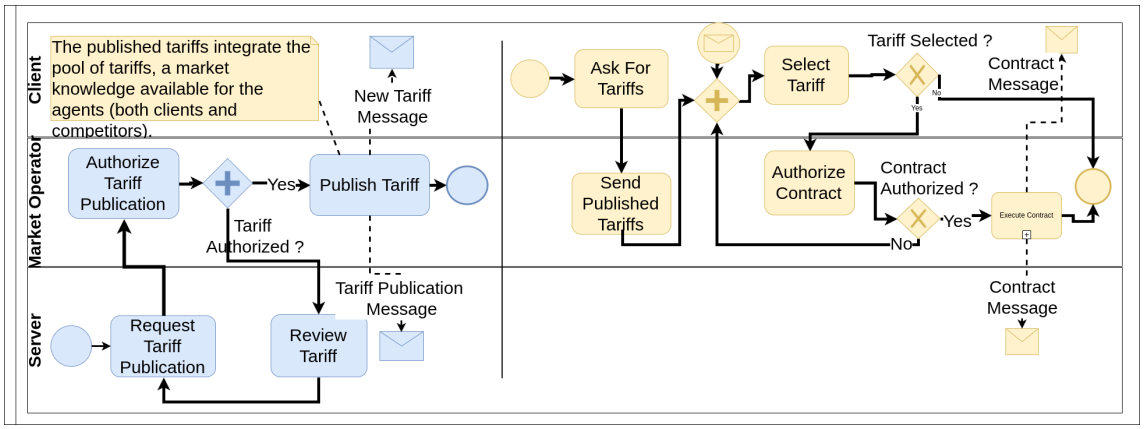


Figure 3.2: Tariff-Based Market Process

Markets operated in a proposal-based fashion follow a different process. Instead of having a pool, the proposals comprise a direct way of establishing a transaction. The agent (customer or provider) creates a proposal requesting a service or good. The market finds the agent that will provide the resource either by selecting a specific agent or initiating a negotiation protocol (sub-process). If a match is established, a contract is consolidated. Figure 3.3 represents proposal-based processes.

Finally, the process of establishing and executing a contract is defined according to Figure 3.4. The service terms (rules) are registered and three main flows might follow in parallel: the client reports provider violations, i.e., the provider does not comply with the contract terms; the converse (client violates the contract); or the service is correctly executed. Occurring the applicable transactions.

The market operator starts the process registering the service terms, corresponding to the contract rules and fees agreed by the parts. Then three main parallel flows might follow. If the client detects a server violation event, i.e., the server do not comply with the contract terms, it automatically reports the situation to the market operator. The same occurs from the server side, if the client violates the contract. Moreover, if an execution event occurs, it is reported by the server. The market operator listens to all these flows and then processes the contract rules in order to assure the corresponding transaction (payment, for example), sending messages to warn the parts. If the end of the contract is reached, the process ends. On the contrary, the flow goes back to wait for new events.

There is no pool of proposals, which are more related to a single occurrence of an event,

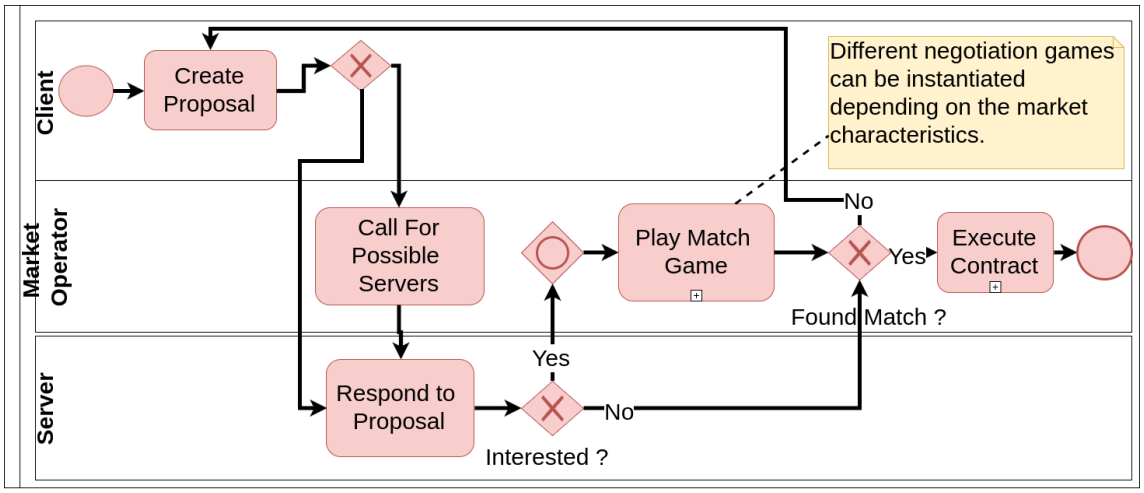


Figure 3.3: Proposal-Based Market Process

more directed to both client and server parts and might include a game for finding the best server for a service (which could include negotiation mechanisms, for example auctions).

The flow starts with the client creating a request. In case the request is part of a direct negotiation, the client also indicates the specific server agent or role it wants to receive the proposal from. On the other way, if no server is specified (or depending on the market characteristics), the requests come first to the market operator so it can create a server-side "Call For Proposal" (CFP). The operator sends the CFP and wait for the interested servers response. In both cases, if no servers are interested on creating a proposal, the flow goes back to the client, so it can review the request terms. In turn, when the market receives the proposals, it starts the game for finding the matching conditions between request and proposals. This game is a different sub-process in each market, allowing the implementation of distinct market possibilities (auctions, direct negotiation, multiple turns of negotiation, discounts, etc.).

Within the end of the sub-process, either a match can be found of not. If there is no agreement, the flow goes back to the customer to review the requirements. On the contrary, the next step is to consolidate and execute a contract, following the same aforementioned contract process.

To the best of our knowledge, there are still no works in modelling market processes. We have used Business Process Modelling (BPM) to describe the processes; for lack of space, we do not include details on how the processes modelled are implemented by the agents.

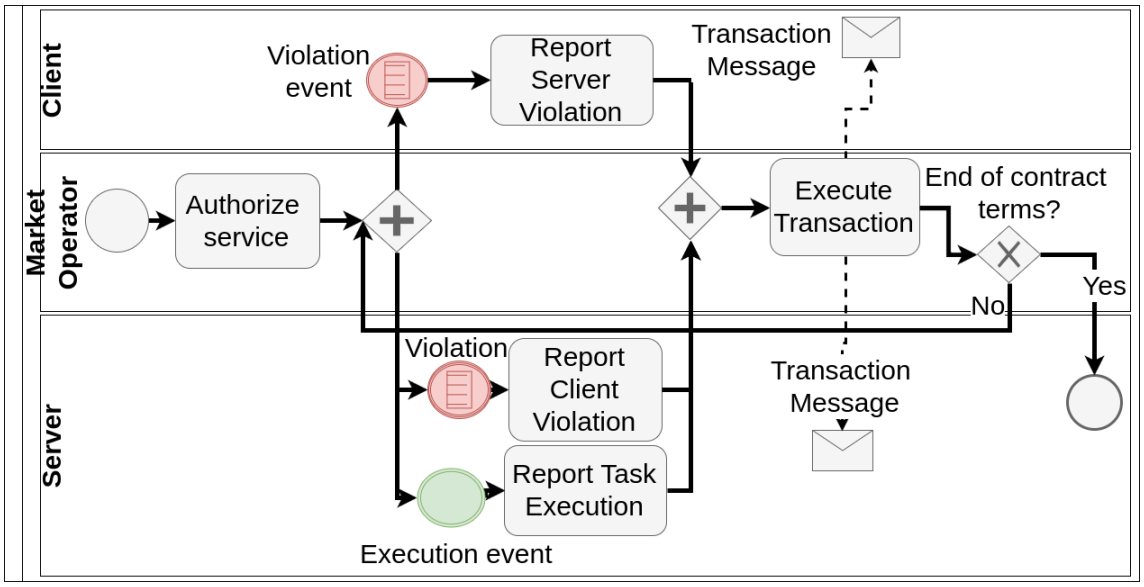


Figure 3.4: Contract Process

3.5 The ResMAS formalization for Home Energy Management

In this section we present a study we performed in [MRK21] of a Home Energy Management (HEM) system according to ResMAS model. HEMs are defined as systems which monitor, control, and optimise the flow and use of energy in the Smart Home environment on top of an Internet of Things (IoT) infrastructure. From an energy demand-side management perspective, improving homes' efficiency without compromising comfort depends on an infrastructure for monitoring energy consumption as well as a strategy for the coordination of appliances. In our HEM system we consider two type of agents: i) the Appliance Scheduler (AS) and the Home Energy Manager (HEM) agents.

The AS agents $as = \{1, ..n\} \subset C$, assuming the customer role, are in control of a specific appliance. AS agents participate in a day-ahead proposal-based negotiation process with the intention of scheduling their appliance's daily electricity consumption.

HEM agents, on the other hand, are the ones responsible for purchasing electricity from a retail or wholesale market according to the needs of AS agents. Each smart house has only one HEM agent associate with; its role is to mediate the negotiation protocol that allows AS agents to derive an energy consumption schedule. In addition to this, deployment of the HEM agent enables homeowners to select one energy regulation policy such as: *Bill*, *Green*, or *Comfort*. Accordingly, the HEM agent will select the set of daily energy consumption proposals that complies with the regulation policy's restrictions, set by the homeowner, as

well as the critical satisfaction level of all AS agents. We can consider the aggregation of various HEM systems as a proposal-based virtual market.

3.5.1 Resources and Markets in Home Energy Management

In ResMAS, a resource is built on two concepts: the resource type, and a countable unit. In our market-based model resource r is defined as the *electricity consumption* in *kilowatts* (3.9). In practice, agents in the HEMS negotiate and, thereby, schedule the consumption of resource instances.

$$Rs = \{\langle ENERGY, kW \rangle\} \tag{3.9}$$

Electricity resources move through two distinct markets (3.10), depicted in Figure3.5, each characterised by their allowed participants, artefacts, regulation mechanisms and processes that describe resource allocation mechanisms.

The m_1 market (3.11) is the source market for energy resources, whereby Home Energy Manager (HEM) agents, each associated with one home, can purchase electricity from Energy Suppliers (3.12). For the sake of simplicity, we make no distinction between Energy

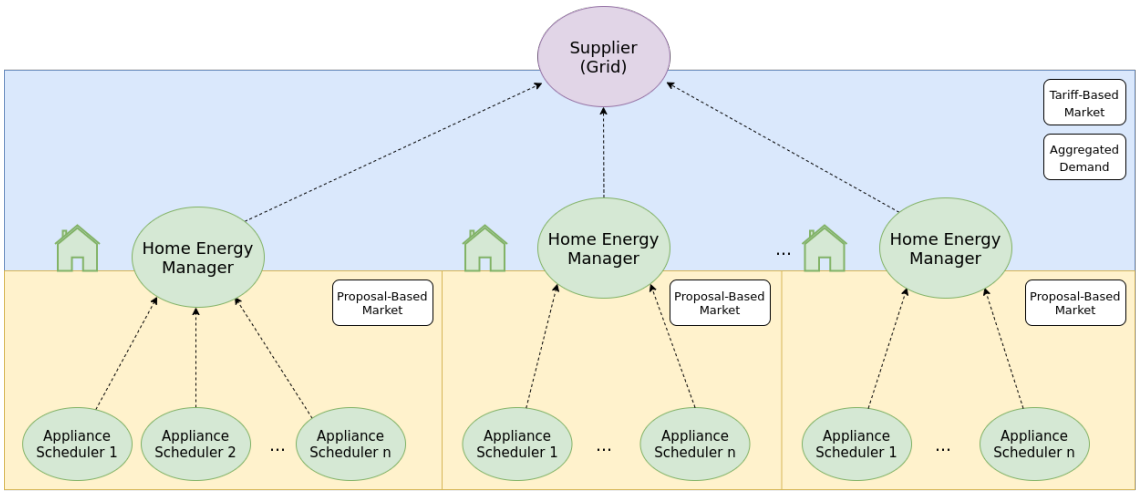


Figure 3.5: Markets considered in the model.

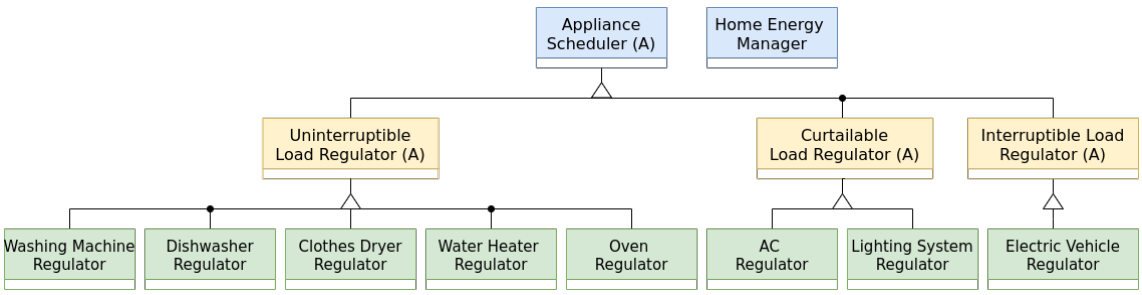


Figure 3.6: Agent Class model corresponding to the m_2 market.

Suppliers and Energy Providers and consider the latter agents to encapsulate both roles. m_1 is further characterised as a tariff-based market in which low volumes of resources are exchanged following the announcement of payment rates in a day-ahead fashion. In this regard, we do not impose any fees in the m_1 market. We classify its tariffs (3.13) simply in terms of *Rates*, that is, an association between each hour of the day and the corresponding prices of a unit of energy resource. Hence, the Supplier agent transacts instances of resources to the HEM agents at each hour (see (3.14)), following the established contract (3.15). The latter, in turn, become accountable for the payments (3.16) corresponding to these transactions, which are computed based on the announced *Rates*.

$$M = \{m_1, m_2\} \tag{3.10}$$

$$\begin{aligned} m_1 =& \langle Part_1, \{tariffs_1, transactions_1, contract_1\}, \\ & SimpleAuthorization, TariffBased\rangle \end{aligned} \tag{3.11}$$

$$Part_1 = \{Supplier, HEM\} \tag{3.12}$$

$$\begin{aligned} tariffs_1 = \langle Rates, Fees\rangle = \langle\{\langle r, 1€, 0h\rangle, ...\}, \emptyset\rangle, \\ s.t.\ r \in Rs \quad \& \ |Rates| = 24 \end{aligned} \tag{3.13}$$

$$\begin{aligned} transactions_1 = \{\langle Supplier, HEM, 10kW, 0h\rangle, ...\} \\ s.t.\ |transactions_1| = 24 \end{aligned} \tag{3.14}$$

$$\begin{aligned} contract_1 =& \langle Parties, Service, Obligations\rangle = \\ & \langle\{Supplier, HEM\}, transactions_1, payments_1\rangle \end{aligned} \tag{3.15}$$

$$payments_1 = \{2€, 3€, ...\}\ s.t.\ |payments_1| = 24 \tag{3.16}$$

$$\begin{aligned} m_2 = \langle Part_2, \{proposal_2, transactions_2\}, \\ SimpleAuthorization, ProposalBased\rangle \end{aligned} \tag{3.17}$$

$$Part_2 = \{HEM, AS\} \tag{3.18}$$

$$proposal_2 = \{\langle 20kW, 0h\rangle, ...\}\ s.t.\ |proposal_2| = 24 \tag{3.19}$$

$$\begin{aligned} transactions_2 = \{\langle HEM, AS, 1kW, 0h\rangle, ...\} \\ s.t.\ |transactions_2| = 24 \end{aligned} \tag{3.20}$$

In the m_1 market,HEM agents purchase resource instances from the Suppliers following the needs of the Appliance Scheduler (AS) agents that engage in the m_2 market (3.17). Each of the latter agents controls a single appliance and participates in a proposal-based negotiation process with the corresponding HEM agent (3.18), leading to a schedule of energy consumption for each appliance. In this scenario, the AS agents put forward proposals of daily energy consumption, as depicted in (3.19), following a Contract-Net protocol. As the result of this negotiation, the $transactions_2$ (3.20) set reports the daily energy consumption profile of each AS agent considering, once again, a 24-hour period and the temporal discretization in the order of the *hour*.

3.5.2 Agents in Home Energy Management

From the previous discussion, we can group the various agents into three distinct classes according to their role in the agent-based market (3.21): *Suppliers*, *Home Energy Managers* and *Appliance Schedulers*. First, we consider the *Supplier* agents to have infinite resources so that they can always respond to increasing demand, as given by the second property in (3.22). Following the ResMAS model, the third property specifies that these agents do not require any resource to operate, as they are just producers and never consumers of resources. Our model does not impose any goal-set Γ_1; nonetheless, this constitutes a research direction for Game Theory-based studies focused on the m_1 market.

As of the second agent-class, a_2, the HEM agents (3.23) are the ones responsible for purchasing energy in m_1 whenever the availability of solar energy is not sufficient to meet the AS agents' needs ($Req^t \equiv P^t_{load}$). The availability ($Avail$) of resources is not only dependent on the home's energy-production capacity (P^t_{PV}, kW), driven by photovoltaic panels, but also on a fixed maximum energy-load permitted at each hour (P_{max}). According to the consumer's preference, the HEM agent may adopt one of three goals Γ_2 (3.24): *Bill* (3.25), considering the unit price of energy as announced by the supplier (p^t), *Green* (3.26) or *Comfort* (3.28).

This model also incorporates the concept of *satisfaction*, given in [APPJ10]. In this regard, the HEM agents are characterised by a critical satisfaction value, given by the consumer, in the $[0, 100]$ interval, where 100 corresponds to the maximum satisfaction. Furthermore, HEM agents are subject to the constraint that the output of their goal function must always be equal to or greater than their critical satisfaction value. It is the role of the consumer to define the satisfaction function of the HEM agent depending on one of the three criteria given above. In contrast to [APPJ10], the satisfaction level depends on the selected regulation criteria, and not on the power being generated at the Smart Home. In addition, we do not employ one agent per energy generation device. Instead, we consider that the HEM agent is aware of all the energy sources and entitled characteristics (energy tariffs, production capabilities, etc), both inwards (the solar panel), as well as outwards (the supplier).

Similarly, a critical satisfaction value C also characterises the Appliance Scheduler agents (3.29). Given by the consumer, it is always compared against the output of a satisfaction function S which directly maps to the agents' goals (3.31), and allows us to define the preferences Π_3 of the agent over the possible schedules of the appliance. As the satisfaction function depends on the type of appliance being controlled by the a_3 agent (3.32), we further

subdivide this agent class into three distinct classes, as given in Figure3.6.

In our model, we distinguish Uninterruptible, Curtailable, and Interruptible Loads [BZ15]. The assignment of appliances to these categories lacks consensus, however, for this initial modelling scenario, we opted for the one that can be inferred by inspection of the agent class diagram. Thus, we have ascribed distinctive characteristics to each of these categories, giving rise to some beliefs of the corresponding agents.

Firstly, a fixed power consumption value (measured in kilowatts) and a cycle duration (measured in hours) characterise the Uninterruptible appliances. Agents related to this category are given static knowledge as of the consumer's preferences, namely: the *Earliest* (EET), *Required* (RET) and *Latest* (LET) end-times that the appliance's operation should comply with. Thus, the satisfaction of an agent of this category is given as a function of the *actual* end-time (x) in relation to the three other values provided by the consumer (3.33).

The Curtailable appliances, as opposed to the previous ones, are capable of regulating mid-operation the power they consume, so they are caracterised by *minimum* and *maximum* power-consumption values. When it comes to the consumer's preferences, the latter should indicate the *start* and *end* times for the operation of this type of appliance, assuming it will always be working within said period. Agents in charge of regulating these appliances will compute their satisfaction as a function of a *characteristic variable* (x), as given in (3.34). In the case of the *Lighting System* and the *AC* agents, given in Figure3.6, their satisfaction depends on the *illuminance* and the *temperature* levels, respectively. Again, this function also takes into consideration the consumer's preferences in terms of *minimum* (MIN), *required* (REQ) and *maximum* (MAX) values for the characteristic variable.

The ability to interrupt and resume the operation at a later time is what distinguishes the third category of household appliances. Hence, Interruptible appliances are defined by a fixed power consumption value and the *start* and *end* times which qualify the period within which they are allowed to operate. As for this category, we illustrate the particular case of the electric vehicle, which is further described by a charging rate (in % per hour). Again, the consumer must supply the *minimum* (MC) and *required* (RC) charge levels that give rise to the corresponding agent's satisfaction function (3.35). Therefore, we consider that the characteristic variable will be the final charge of the vehicle at the end of the period allowed for recharging.

$$A = \{a_1, a_2, a_3\} \tag{3.21}$$

$$a_1 = \langle Supplier, \infty, \emptyset, \Gamma_1 \rangle \tag{3.22}$$

$$a_2 = \langle HEM, Avail, Req, \Gamma_2 \rangle \tag{3.23}$$

$$\Gamma_2 = \{\gamma^1, \gamma^2, \gamma^3\} \tag{3.24}$$

$$\gamma^1(Bill) : min\, F = \sum_{t=0}^{23} p^t.(P^t_{load} - P^t_{PV}).h^t$$
$$s.t.\, P^t_{load} \leq P_{max} \quad \& \quad S_{HEM}(F) \geq C_{HEM} \tag{3.25}$$

$$\gamma^2(Green) : min\, F = \sum_{t=0}^{23} (P^t_{load} - P^t_{PV}).h^t$$
$$s.t.\, P^t_{load} \leq P_{max} \quad \& \quad S_{HEM}(F) \geq C_{HEM} \tag{3.26}$$

$$h^t = \begin{cases} 0 & \text{if } P^t_{load} \leq P^t_{PV} \\ 1 & \text{if } P^t_{load} > P^t_{PV} \end{cases} \tag{3.27}$$

$$\gamma^3(Comfort) : max\, F = \sum_{i=1}^{N_{AS}} S_{AS}(AS_i)$$
$$s.t.\, P^t_{load} \leq P_{max} \quad \& \quad S_{HEM}(F) \geq C_{HEM} \tag{3.28}$$

$$a_3 = \langle AS, \emptyset, Req, \Gamma_3, App, \Pi_3 \rangle \tag{3.29}$$

$$Req = \{\langle 0h, 1kW \rangle, ...\}\, s.t.\, |Req| = 24 \tag{3.30}$$

$$\Gamma_3 : max\ S_{AS}\ s.t.\, S_{AS} \geq C_{AS} \tag{3.31}$$

$$App \in \{WashingMachine, DryerMachine, ...\} \tag{3.32}$$

$$S_{unint} = \begin{cases} 0 & if & x < EET \\ \frac{100.(x-EET)}{RET-EET} & if & EET \leq x \leq RET \\ \frac{100.(x-LET)}{LET-RET} & if & RET < x \leq LET \\ 0 & if & x > LET \end{cases} \tag{3.33}$$

$$S_{curt} = \begin{cases} 0 & if \quad x < MIN \\ \frac{100.(x-MIN)}{REQ-MIN} & if \quad MIN \leq x \leq REQ \\ \frac{100.(x-MAX)}{MAX-REQ} & if \quad REQ < x \leq MAX \\ 0 & if \quad x > MAX \end{cases} \tag{3.34}$$

$$S_{int} = \begin{cases} 0 & if \quad x < MC \\ \frac{100.(x-MC)}{RC-MC} & if \quad MC \leq x \leq RC \\ 100 & if \quad x > RC \end{cases} \tag{3.35}$$

3.5.3 Experiments in Home Energy Management settings

The following experimental setting and results derive from our work[1] in [MKR22]. Now, let's consider a smart home scenario composed of various appliances. The features of each of these appliances are defined according to the corresponding appliance category. For example, while Uninterruptible Appliances are characterised by a fixed power-consumption value, Curtailable Appliances are ascribed a power-consumption range. These features are preserved across all simulations. Furthermore, Curtailable appliances are defined by a function that takes as input a certain level of characteristic variable, plus additional parameters that depend on the appliance itself, and outputs the power required to achieve said level of satisfaction. Accordingly, the bulbs that compose the Lighting System have a corresponding Luminous Efficacy level, while the Sound System has a corresponding Sensitivity Rating level. As for the Electric Vehicle, the simulations consider that it presents a charge value of 50% at the start of the day-ahead negotiation process. It is also important to note that no appliances were dropped from any simulation, meaning that a single Smart Home environment was considered throughout the simulations.

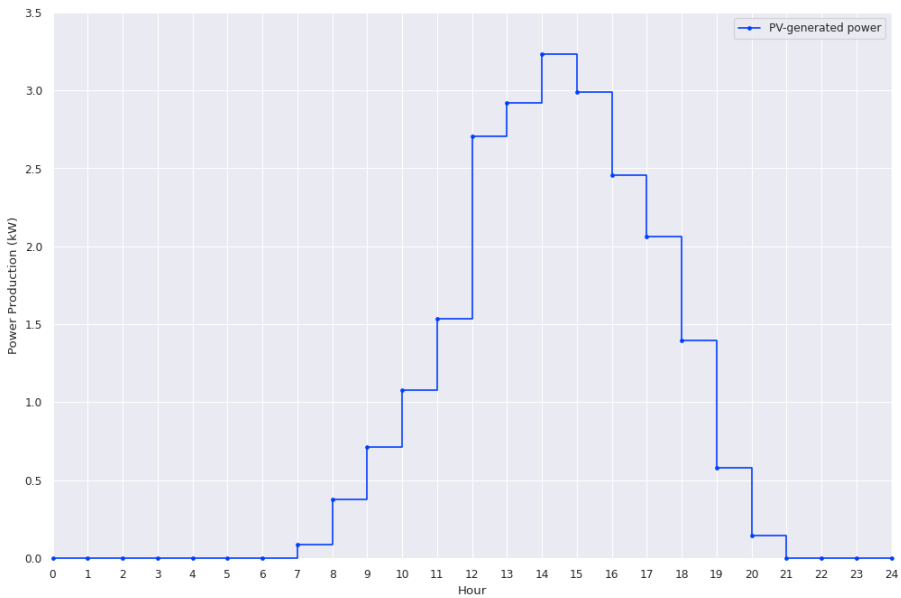


Figure 3.7: Hourly-power production of photovoltaic panels with 4kW capacity.

[1]The study is under review in the IEEE Transactions on Systems, Man and Cybernetics: Systems

The Smart Home scenario also integrates a photovoltaic panel (PV) with a capacity of 4kW. The PV's hourly-power dataset was generated with the Renewables.ninja simulation tool. The result of our simulation, illustrated by Figure 3.7, was built into the HEM agent's knowledge base.

Despite the availability of photovoltaic energy in the Smart Home, its energy production capacity is not sufficient to meet the consumption needs of all the appliances. Thus, to meet the total energy demand, the remaining energy needs to be purchased from a provider. Typically, energy providers advertise various energy tariffs. This is the case of EDP, an energy company operating in Portugal. The tariffs employed in the simulations - Simple, Dual-Rate and Triple-Rate - which are plotted in Figure 3.8, are based on the tariffs advertised by this energy provider.

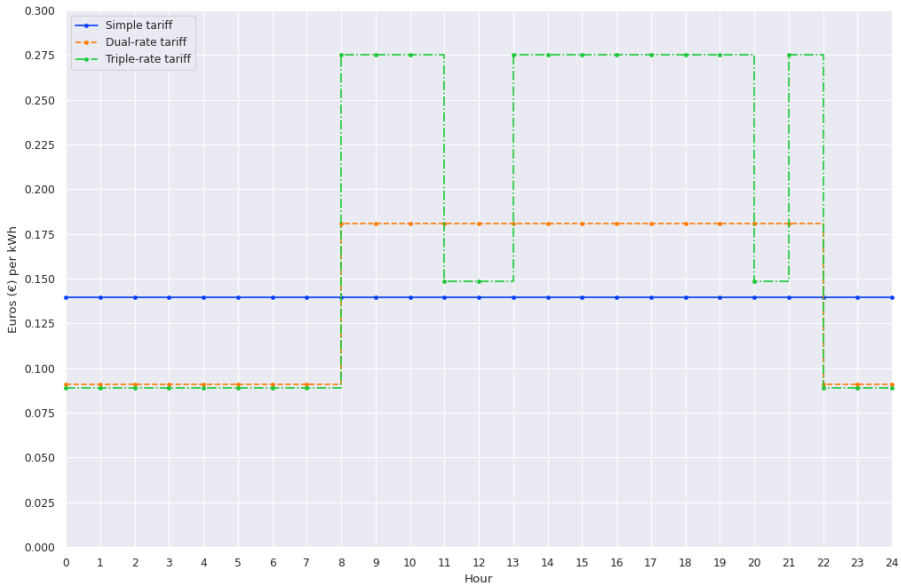


Figure 3.8: Hourly-tariffs considered in the simulations: Simple, Dual-Rate and Triple-Rate.

Additional restrictions are imposed on the Smart Home environment. First, the maximum peak power supported is set to 6kW. This information is included, together with the hourly prices of energy and the PV's hourly power production capacity, in the HEM agent's knowledge base. In addition, the latter agent is tailored to decrease the requested satisfaction level by 5% among consecutive iterations of the negotiation protocols (Anticipate and Emergency). However, in order for the negotiations to be successful, the requested satisfaction can only be lowered up to a 50% satisfaction level, which is set as the critical satisfaction level of all the appliances, among all the simulations.

3.5.3.1 Comfort Regulation Scenario

As of the first simulation, attention was drawn to the Comfort regulation policy. This proved to be a good starting point to gather *baseline* results. With this simulation, it was intended to observe whether it would be possible for the HEM Agent to achieve 100% satisfaction, thus reflecting a maximum satisfaction of all scheduler agents. A priori, this scenario may not be achievable by exceeding the maximum electrical-circuit power that may

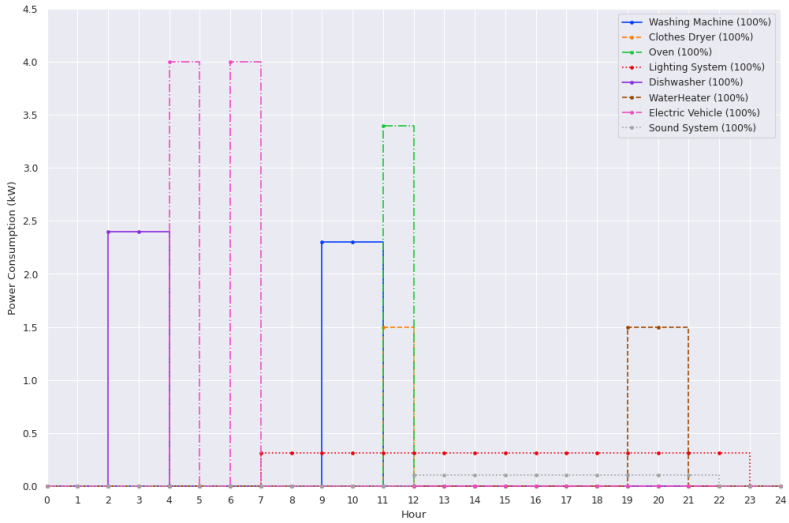


Figure 3.9: Appliances' scheduling under the comfort regulation scenario.

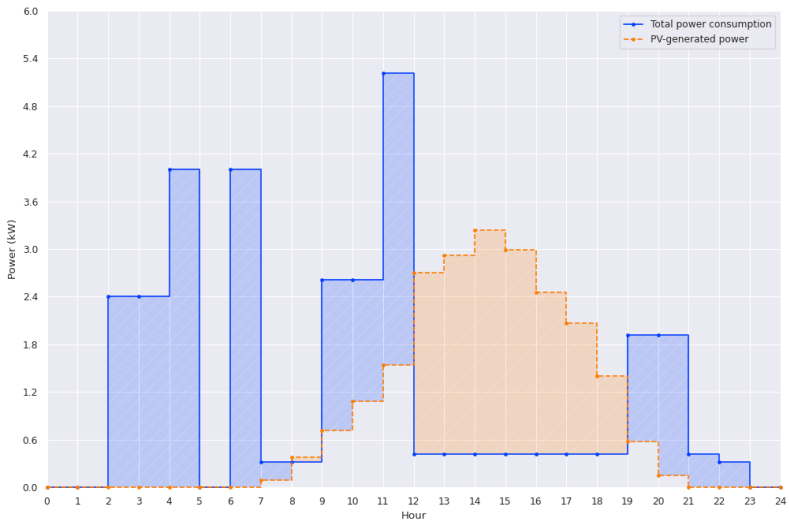


Figure 3.10: Total power consumption against PV-generated power under the comfort regulation scenario.

flow at any given time (set to 6kW). For this simulation, a dual-rate tariff was adopted.

The results obtained from this simulation are presented in Table 3.1. Figures 3.9, 3.10 and 3.11 also support the analysis of the results. It proved to be possible, given the consumer preferences introduced earlier on, to schedule the appliances in a matter that resulted in the maximum average satisfaction for all, a value that is equivalent, in the case of the selected regulation policy, to the satisfaction of the HEM Agent. In plot 3.9, which depicts the scheduling of all the appliances, the satisfaction of each of them is given in parenthesis in the legend.

The Comfort Regulation Policy is unconnected to the consumer's budget and also to the energy produced by the PV. For this reason, it is valid to assume that a scheduling resulting from this policy would attain the highest daily energy expenditure. In fact, when

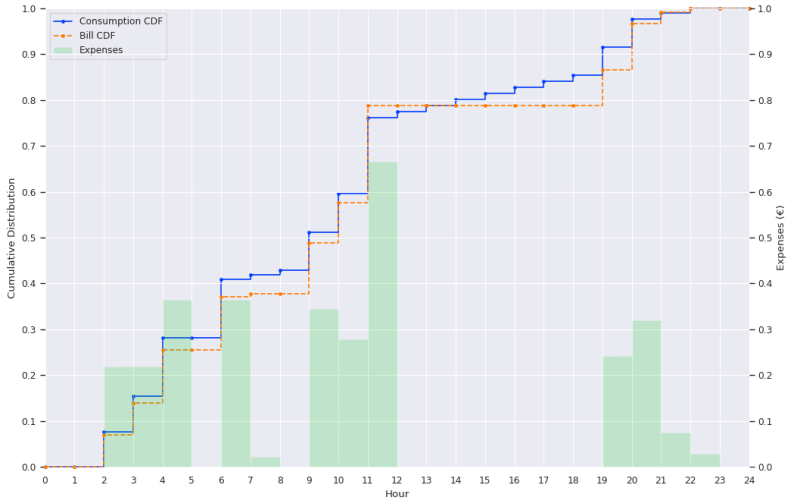


Figure 3.11: Cumulative distribution functions and hourly spendings under the comfort regulation scenario.

considering a dual-rate tariff, the costumer would have to be willing to spend around 3 euros a day to maximise its comfort, following an hourly distribution of these expenses as given in Figure 3.11.

The energy generated by the PV is also not well exploited, as only about 33% of the energy it generates is used to support the home's energy needs. Figure 3.10 provides a visual representation of this phenomenon. The remaining percentage corresponds to wasted energy, given that an energy storage system was not considered for this scenario. Thus, around 77% of the energy needs of the home would have to be satisfied by energy purchased from the provider.

Table 3.1: Results of the Comfort Scenario simulation.

Peak Load (kW)	5.2130
Total Energy Consumption (kW)	31.3280
Energy taken from Grid (kWh)	23.9730
Energy taken from PV (kWh)	7.3550
Energy wasted from PV (kWh)	14.9180
HEM's satisfaction	100.0000
Average Appliance Satisfaction	100.0000
Total Bill (euros)	3.13869

3.5.4 Bill Regulation Scenarios

Through a cost-based regulation policy, we will assume that the consumer may establish a contract covering a simple or dual tariffs.

Simple tariff In the first simulation of this type of policy, the Simple tariff is considered, such that the energy price remains at 0.13961€ per kWh throughout the day. Moreover, the consumer restrictions are set to 50% critical satisfaction, and the budget interval to $[0, 6]$ euros, meaning that the consumer is willing to spend a maximum of 6 euros for the energy bought from the provider in the scenario of greatest compromise, that is, the one in which the critical satisfaction is zero.

As a result, the HEM Agent's satisfaction from the day-ahead negotiation with the Scheduler agents is set close to the critical satisfaction, as given in Table 3.2. The scheduling of the appliances is more efficient compared to the one obtained under the Comfort policy (coupled with a dual-rate tariff), as about 50% of the energy generated by the panel is effectively used. Still, around 67% of the home's energy needs are supported by the energy purchased from the provider.

We then simulated a new scenario by changing only the critical satisfaction of HEM Agent from 50% to 20%. As a result, the system yielded a scheduling equal to the one yield under a Comfort regulation strategy (coupled with a dual-rate tariff), where all appliances reach 100% satisfaction. However, a difference is noticed between the two scenarios. It can be concluded that, according to the consumption preferences, the consumer would benefit from choosing a dual-rate tariff, as this would enable him/her to save around 20 cents. However, if the consumer is willing to compromise on comfort, for an average appliance satisfaction value of 69%, he/she will further save 18 cents, reaching a daily expenditure of less than 3 euros.

Table 3.2: Results of the Simple Tariff Scenario simulations.

	Simple Tariff (C.S. 50%)	**Simple Tariff (C.S. 20%)**
Peak Load (kW)	5.32400	5.21300
Total Energy Consumption (kW)	31.43600	31.32800
Energy taken from Grid (kWh)	21.15700	23.97300
Energy taken from PV (kWh)	10.27900	7.35500
Energy wasted from PV (kWh)	11.99400	14.91800
HEM's satisfaction	50.77119	44.21882
Average Appliance Satisfaction	69.00000	100.00000
Total Bill (euros)	2.95373	3.34687

Dual-rate tariff Consumers can establish dual-rate tariff contracts and schedule the operation of their electrical appliances (in general, those of higher consumption) for hours when the price of energy is lower. Simulations were also performed regarding this type of tariff, considering the following prices: 0.18090 euros/kWh and 0.09110 euros/kWh for peak and off-peak hours, respectively. All the other simulation parameters (including consumer preferences and appliance characteristics) were preserved in order to find out which tariff best fits the preferences of this type of consumer.

The results show (see Table 3.3) that the simulation with 20% critical satisfaction yields the same scheduling of appliances as in the results of the scenario Simple Tariff with C.S. set to 20 %. However, this scheduling results in a satisfaction of around 48% for the HEM Agent as opposed to 44% under the latter scenario.

Table 3.3: Results of the Dual-Rate Tariff Scenario simulations.

	Dual-Rate Scenario (C.S.: 50%)	**Dual-Rate Scenario (C.S.: 20%)**
Peak Load (kW)	4.00000	5.21300
Total Energy Consumption (kW)	31.43600	31.32800
Energy taken from Grid (kWh)	22.70400	23.97300
Energy taken from PV (kWh)	8.73200	7.35500
Energy wasted from PV (kWh)	13.54100	14.91800
HEM's satisfaction	51.52345	47.68844
Average Appliance Satisfaction	71.12500	100.00000
Total Bill (euros)	2.90859	3.13869

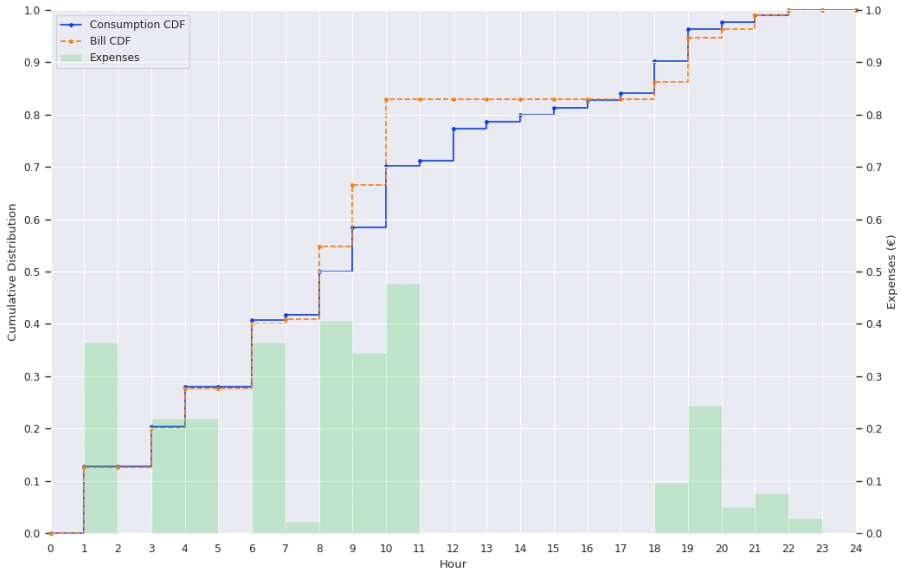


Figure 3.12: Cumulative distribution functions and hourly spendings under a scenario with Bill regulation, 50% critical satisfaction and Dual-Rate tariff.

The results obtained with a higher satisfaction value prove to be more interesting, as they show that the adoption of a dual-rate tariff leads to a scheduling that yields not only lower daily costs for the consumer (2.90859 euros, as opposed to 2.95373 euros), but also greater comfort. This reasoning leads to conclude that the latter result totally dominates those obtained under simple tariff conditions.

It is also worth noticing that the present case study, despite taking less advantage of the energy generated by the PV, still enables the lowest daily costs. The reason behind this result has to do with the off-peak prices. According to EDP's recommendations, consumers should consider this pricing strategy whenever the off-peak period alone accounts for more than 40% of the total energy consumption. The present simulation proves that it is possible to achieve a power consumption profile that satisfies this condition, such that the Dual-Rate tariff proves to be monetarily beneficial. We can deduce the satisfaction of this condition by looking at Figure 3.12.

3.6 Summary

This chapter describes an integrated conceptual architecture for market-based scenarios where traditional market organizations are complemented by emerging marketplaces. In this area, there is very diverse literature, depending on the application domain. New market structures are emerging, propelled by the recent technological advances. The possibilities of applying market-based approaches to enable coordination and provide improvements on the ancillary services are even broaden when considering the high correlation with multi-agent systems. Different market models are possible: wholesale, retail, bilateral, virtual markets, peer-to-peer, etc. Thus, there was a lack for an integrated architecture that enables the analysis of how interactions in owe market can affect others and how entities participate in multiple markets. A model that discusses how different markets of the same domain interact and analyses the impact of participation in multiple markets, has not been previously fully considered. For this reason we present the ResMAS conceptual architecture using the Multi-Agent Systems metaphor.We describe the market processes, modelled using BPMN, to show the orchestration of the activities in two market flows: tariff-based markets and proposal-based markets. Furthermore, we present a formalization of a market structure based on ResMAS as an enabler for control and usage coordination of the shared resources for HEM systems. The strength of this work lies in a conceptual model that explores the rich semantics of the MAS paradigm to represent the complexity inherent to socio-technical systems such as sustainable houses. A preliminary simulation study performed on the HEMS confirmed the potential of the solution towards sustainability. We show that a HEM implementation following the ResMAS model can aid the consumer in decision making and raise homeowners' awareness as of their resource consumption profiles, and provoke behavioral changes leading to more sustainable consumption patterns and thus to an increase of the agents' social welfare.

Chapter 4

Simulating Collective Decision-Making: Leveraging Social Coordination of Autonomous Vehicles through Vehicular Networks

4.1 Introduction

Autonomous driving has gained momentum in recent years due to impressive technological advances put forward by both academic and industrial companies. Currently, automotive manufacturers and tier 1 suppliers are designing, building and testing automated vehicles that navigate in complex scenarios without the explicit intervention of human drivers or other vehicles [ZBSea14]. In parallel, advances in vehicular networks have enabled explicit cooperation between vehicles using Vehicle-to-Vehicle communications (V2V) and between vehicles and infrastructure through Vehicle-to-Infrastructure (V2I) communications. In this context, cooperation is established by the periodic or event-driven exchange of static and dynamic data (e.g. location, trajectories) through wireless networks, e.g. through Cooperative Awareness Messages (CAM) [Bd16, dB14].

MAS research has devised various social coordination mechanisms, (e.g. voting [PKSA06]) to reach consensus over the agents' aggregated preferences. For instance, within vehicular applications, voting mechanisms have been applied for reaching agreement in car-sharing [DM16], platooning [TdK18] and leader election in distributed intersection control [FFC+10]. However, the vast majority of the experiments or simulations do not account for a wide spectrum of constraints that Connected Automated Vehicles (CAVs) will face in real-world deployments (e.g. unreliable communication channel) reducing the representativeness of the results, which constitutes a key gap within the literature of applied MAS solutions for social vehicular coordination.

We argue that the evaluation of social coordination mechanisms for collective decision-making should take into account realistic constraints. In order to expedite the development of MAS-based transportation solutions, these should preferentially be tested in software (i.e. simulation) that capture both kinematic and communication constraints. However, to the best of the our knowledge, no simulation framework that unifies a microscopic traffic simulator, network simulator and MAS development framework is available. In this chap-

ter, we tackle the challenge of unifying simulators of various different domains, programming paradigms and architectures in order to test with social coordination mechanisms in real-world settings for CAVs and study their impacts such as vehicle flow or emissions. We propose a multi-domain simulation framework where Intelligent Transportation Systems (ITS) MAS-based mechanisms can be tested and analyzed. The components of this framework utilize SUMO [LBB+18a] for microscopic traffic simulation, OMNeT++ [VH08] for the network simulation and LightJason [ADKM18] as the MAS framework to empower high-level decision-making. We discuss how the simulation framework execution performance is impacted by varying the number of agents in a simple vehicular coordination scenario where a platoon formation reaches consensus through bargaining negotiation. Finally, we propose the application of computational social choices mechanisms (i.e voting), as potential vehicular agreement mechanisms, to establish cooperative behaviour within a platooning scenario involving autonomous vehicles.

This chapter makes the following contributions:

1. We present the design of an autonomous vehicles simulation framework to test with social coordination mechanisms in real-world settings in presence of vehicular communications;

2. We propose to consider different voting protocols together with committee voting rules as a means of collective decision-making for coordination of autonomous vehicles in platoon formation;

3. We use simulation to empirically analyze the effect of voting mechanisms on the platoon formation and on the social welfare performance metrics from the perspective of the whole system

The remainder of this chapter is organized as follows. Section 4.2 presents the recent state-of-the-art in (integrated) simulation platforms and vehicular coordination. We present a high-level description of the simulation architecture in Section 4.3. Section 4.4 describes the theoretical foundation for the social coordination mechanisms to be tested. The results of the coordination scenarios are described in Section 4.5. Finally, Section 4.6 summarises the main topics of this chapter.

Earlier work of this chapters appears in [TdK20]

4.2 Related Work

4.2.1 Intelligent Transportation Systems Simulation frameworks

Simulation is considered as an effective tool for verifying and evaluating ITS solutions as their practical implementation and deployment requires high cost and intensive labor. In this section, we first briefly review traffic, network and MAS (simulation) frameworks, and then we present selected integrated simulation platforms that have been proposed to study ITS solutions.

4.2.1.1 Individual Simulators and Development Frameworks

The main function of a traffic simulator is to provide an accurate kinematic model of each vehicle as well as interactions between them in virtual traffic environment, to replicate and obtain realistic traffic information. On the other hand, a network simulator mainly focuses on the realistic simulation of message exchange between vehicles in a vehicular network considering communication impairments (e.g. wireless propagation) and protocol constraints.

Microscopic traffic simulators: Traffic simulators are classified into macroscopic, mesoscopic, and microscopic models with respect to the traffic flow resolution they represent. The macroscopic description models gross quantities of interest, such as density or mean velocity of cars, treating vehicular traffic according to fluid dynamics, while the microscopic descriptions consider each vehicle as a distinct entity, modeling its behavior in a more precise but computationally more expensive way. Mesoscopic models combine the properties of both microscopic and macroscopic simulation models. Thus, mesoscopic models provide less details than micro-simulation tools, but offer more flexibility to the typical planning analysis techniques. Since in this chapter we focus on the interaction of individual vehicles as they coordinate their actions in a platooning context, we solely consider microscopic traffic simulators.

Generally speaking, a traffic simulator is composed of four principal components: a) road network topology constraints, b) motion restrictions and driver models, c) traffic and trip generators, and d) visualization tools and other simulator's interfaces. Existing examples of simulators include SUMO [LBB+18a], AIMSUN [CFG+10], PTV Vissim [FV10], Paramics [CD96], VIPS [GDG17], and to some extend MATSim [HNA16]. AIMSUN, VISSIM, and Paramics are commercial products, whilst SUMO and MATSim are open-source projects facilitating the adaptation or development of new features and the integration with other simulators. Passos et al. [PRK11] proposed a taxonomy on the basis of diverse criteria to assess how suitable currently available simulation packages are to model urban transportation systems. A similar analysis has been performed in [SEFE16].

Network simulators provide models to simulate wireless links between nodes (i.e. vehicles) including accurate signal propagation (e.g. channel modeling [VBTV15]) and wireless protocols. Network simulators provide a cost effective validation of network protocols and design, allowing for simulation of the complete protocol stack ranging from the physical layer up to the application layer. Features of network simulators include network topology modeling, traffic flow analysis, performance metric outputs, protocol evaluation, among others. The primary open-source network simulators, which have been also tailored for vehicular network simulation (i.e. include 802.11p/ITS G5 protocols [CMS15, SD14] or vehicular channel models), are OMNeT++ [VH08] and NS-3 [RH10]. Fernandes and Ferreira [FF12] identified the performance and scalability limits of network simulators (specifically NS-3) and propose possible improvements to existing physical and mobility simulation models.

MAS frameworks provide the necessary support for implementing agent-based solutions, similarly to the simulation packages. These frameworks allow for the definition of agent behaviours as well as the actions they have available with which to interact with the environment. Some of the mostly used MAS framework include JADE [BBCP05],

Jason [BH05], LightJason [ADKM18] and Spade [GCB06]. These frameworks have been used to test a number of ITS applications based on the multi-agent paradigm, namely route choice (e.g. [CCF+19]), transport analysis (e.g. [KMR+14, ROB07]), autonomous driving (e.g. [AYA17]), intersection management (e.g. [VO12b, dOBdS+06]), among others. Bazzan and Klügl in [BK14] and Chen in [CC10] provide an extensive literature review of the MAS metaphor application in traffic and transportation systems both as programming and as a modeling paradigm.

4.2.1.2 Integrated Simulators

Individual simulators often fail to provide the necessary tools for a thorough analysis of the system. For instance, vehicle platooning enabled by V2V/V2I communications requires a distributed simulation architecture that tightly couples (vehicular) network simulation with microscopic traffic simulation, including platooning control. In the following, we present in detail well-known integrated simulation platforms for evaluating ITS application.

Microscopic traffic + network simulators: An integration of SUMO and OMNeT++ is presented in the VEINS project [SGD11]. Segata et al introduced the Plexe extension in [SJB+14] to provide VEINS with platooning capabilities. Recently, Mena-Oreja & Gozalvez presented in [MOG18] the PERMIT simulator as an extension of Plexe in order to allow for platooning maneuvers in scenarios involving both automated and non-automated vehicles. The Plexe extension is also used in [HD18] to develop a centralized and decentralized approach to platoon formation. Singh et al. proposed the VENTOS simulation framework, as an integration between SUMO and OMNeT++, in [SSN+18] to implement a leader election protocol for platoons. The integration of a microscopic traffic simulator, DIVERT, and the NS-3 network simulator is proposed in [FdF10] to simulate heterogeneous vehicular networks. A simulation run-time infrastructure is provided by VSimRTI [Sch11] to facilitate network and kinematic modelling of V2X applications.

Microscopic traffic + MAS frameworks: A similar rationale applies in modeling vehicle (or other artifacts such as traffic lights) as autonomous systems. This, usually, results in the integration of MAS frameworks with microscopic traffic simulators. A typical approach consists into delegating low-level control tasks to the traffic simulator, whilst maintaining the high-level decision-making within an agent platform/design. Rossetti et al. combined a microscopic traffic simulator to a belief-desire-intention (BDI) MAS in [RBL+00] to study the drivers' decision-making in commuting scenarios. Soares et al. present the integration of JADE and SUMO in [SKMR13] to build an artificial transportation systems simulation framework where drivers and traffic control can be designed as MAS. In a similar approach, Görmer et al. combined JADE and AIMSUN [GM12]. In [dABC13] a traffic management solution is evaluated using the Jason MAS framework and SUMO.

A summary of the reviewed simulation platforms is presented in Table 4.1 demonstrating that no other simulation platform currently integrated the three simulation types (i.e. traffic, network and MAS).

Table 4.1: Comparison of various ITS simulation frameworks

Framework	Traffic	Network	MAS
VEINS [SGD11][SJB+14]	X (SUMO)	X (OMNeT++)	
PERMIT [MOG18]	X (SUMO)	X (OMNeT++)	
VENTOS [SSN+18]	X (SUMO)	X (OMNeT++)	
VNS [FdF10]	X (DIVERT)	X (NS-3)	
VSimRTI [Sch11]	X (SUMO)	X (NS-3/...)	
Soares et. al [SKMR13]	X (SUMO)		X (JADE)
Görmer et al. [GM12]	X (AIMSUN)		X (JADE)
Batista et al. [dABC13]	X (SUMO)		X (JADE)
Proposed	**X (SUMO)**	**X (OMNeT++)**	**X (LightJason)**

4.2.2 Collective Decision-Making for Platooning

Within the field of traffic simulation there is already a significant amount of literature concerning both platooning and autonomous vehicles and their interaction. Nevertheless, there are still some interesting topics in need of further study and analysis, namely the decision-making process into achieving consensus and coordination in platoon coalitions among vehicles.

A control framework to allow for the organization of AVs into organized coalitions is given in [MA13]. Outside of the coalition organization of AVs, many other cooperative solutions are presented. Manzinger et al. presented an approach based on reachability analysis in [MA17] to allow any collaborative AV to negotiate safe driving areas. Maneuver templates are used in [MLA17] for use in cooperative strategies. Yang et al. consider a game theoretical approach in [YZJL16] to solve lane-merging conflicts between a pair of AVs. Shou-Pon et al. demonstrate a novel lane merging in [LM16] to solve conflicting situations. Rewald et al. explore the use of auction-based control in [RS16] to achieve cooperative behavior among autonomous vehicles, while taking into account the personal objectives and preferences of the auction participants. Domingues et al. consider a bargain negotiation protocol in a lane-merging platoon application [DCM+18]. Santini et al. has analyzed and explored the use of a distributed consensus algorithm to maintain stability in the platoon while maneuvers are performed and the topology of the platoon changes [SSV+19].

One specific field of interest is the application of voting systems to achieve consensus. Recently, Wu et al. presented a mechanism in [WWW19] to allow measuring the trust of platoon leaders using centralized data management centers, while Singh et al. implemented an incentive based leader election protocol [SSN+18]. Voting mechanisms for leader elections have been used in vehicle coordination for intersection management scenarios as in Ferreira et al. [Fer12]. Vehicular coordination is achieved using consensus mechanism for the vehicle leader election in [ALV17]. Another specific sub-filed of interest is the definition of platoon characteristics (e.g. route, speed). Teixeira et al. discuss and compare the most common voting mechanisms based on single candidate and committee elections to study the effects of voting on the platoon's welfare [TdK18].

However, other types of coordination problems also exist. Dennisen et al. proposed an agent-based voting architecture for traffic applications and theorized possible applications

for taxi-sharing and platooning scenarios [DM15]. In [DM16] iterative committee elections are considered for reaching consensus in ride-sharing applications. Another example is the application of coordination strategies to overcome unreliable inter-vehicle communications [JN16].

To the best of our knowledge, the simulation framework proposed in this chapter is the first work to include selected real-world constraints, such the vehicular kinematics and communication impairments (e.g. packet loss), to ITS MAS-based solutions.

4.3 A Simulation Framework for Vehicle Coordination

Any potential coordination mechanisms applied to CAVs are subject to rigorous validation before deploying on the field. As such, properly tuning and even filtering out of mechanisms in an early state of development (e.g. software simulation phase), allows for shortened development time and reduced costs. However, proper software validations require that the models utilized by the simulation framework be as representative as possible of the real world, in order for the testing to be valid. This imposes multiple constraints within the framework.

4.3.1 Overview of Architectural Components and Interactions

One of the first constraints to be taken in account is kinematic physical constraints that exist within vehicular environments. When a vehicle agent decides to perform a given maneuver, the agent must first ensure that such maneuver is possible and even if its safe to do so. For example, an overtake maneuver requires that a lane be available and that overtaking is allowed within the current road stretch. Even if such conditions are met, temporal factors must be taken into account. An overtake maneuver will take time to perform, during which environment conditions can change, such as an undetected obstacle in the road appearing in the passing lane. Due to the non-deterministic environment, many restrictions are made on the decision-making process of the agent. To ensure such fine-grain validation of the kinematic constraints imposed on agent-based mechanisms, a microscopic traffic simulator is needed.

Another component adding onto temporal constraints is the communication medium of cooperative vehicular networks. A MAS-based coordination mechanism needs to implement a communication protocol that is adequate for communications in vehicular (ad-hoc) networks. A mechanism that relies on exchanging various messages and large quantities of information will add latency problems, even if said mechanism would lead to high welfare. Coordination mechanisms should be able solve conflict scenarios as fast as possible in order to prevent unsafe scenarios of occurring. The communication medium in which vehicular communications occur (i.e. the wireless medium) is relatively unreliable, and requires many fail-safe mechanisms and contention control algorithms in order to ensure proper delivery of messages. The communication delay is induced by the mechanisms needed to ensure receipt of messages as well as the communication protocol involved. To account for this, a network simulator is needed in order to validate coordination mechanisms according to

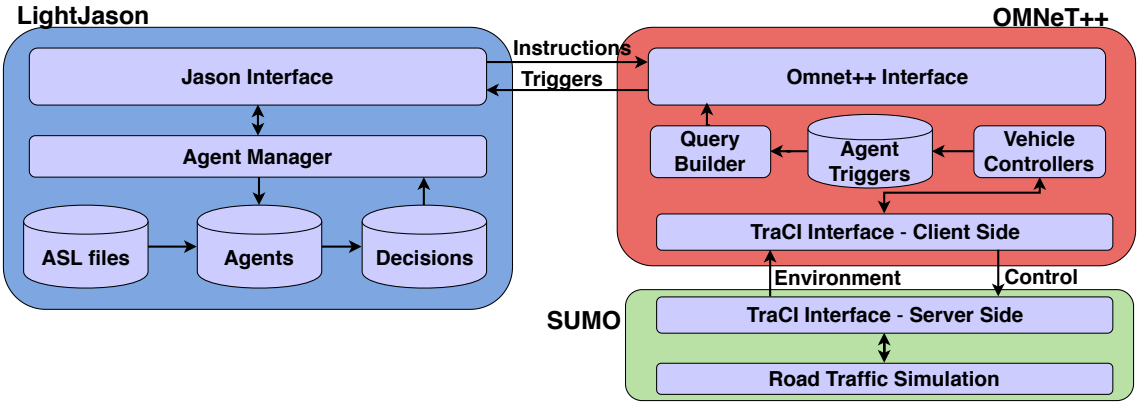


Figure 4.1: High-level architecture of the proposed simulation framework

their communication overhead. Preferably, the network simulator should include models on the literature standard IEEE 802.11p and IEEE 1609.4 DSRC/WAVE (ITS G5) protocol stack. However, it should also be extensible to future communication networks, such as, next-generation cellular (5G) or ad-hoc networks.

With a traffic and network simulator, constraints can be modelled and validations can be approximated to as close to reality as possible. The final component is, of course, the MAS framework in which the high-level processes of the a coordination mechanism are defined. The run-time of the MAS framework will manage and create the agents associated to each vehicle. These agents contain a high-level knowledge on the environment and create the high-level plans that the vehicle should execute. The production and processing of information will mostly occur within the agent. Information produced by the agent can either be handed over to the i) network simulator to be encapsulated and sent over to other nodes through wireless (ad hoc) vehicular networks; or to the ii) traffic simulator to be converted into low-level instructions (e.g. change vehicle speed) for vehicle control (following the concept of delegate agent in [SMKR, SKMR13]). The opposite flow of actions must also occur: i) messages received in the network simulator are processed and sent to the agent; and ii) kinematic and traffic information in the traffic simulator is sent to the agent.

4.3.2 Simulation Framework Development

Figure 4.1 presents a high-level architecture of the simulation framework. The first selected simulator for the framework is the microscopic traffic simulator **SUMO**[1], which simulates the kinematic motion of vehicles as well as the traffic environment in which vehicles travel through. Communicating directly with SUMO via TCP socket connection (using its **TraCI interface**), is **OMNeT++**[2], an event-based (ii) network simulation that models the communication media and protocols. OMNeT++ simulates the wireless network of autonomous vehicles, including the physical layer, and implements the standard communication protocols (e.g. IEEE 802.11p) used in vehicular communications. The pro-

[1] http://sumo.dlr.de/index.html
[2] https://omnetpp.org/

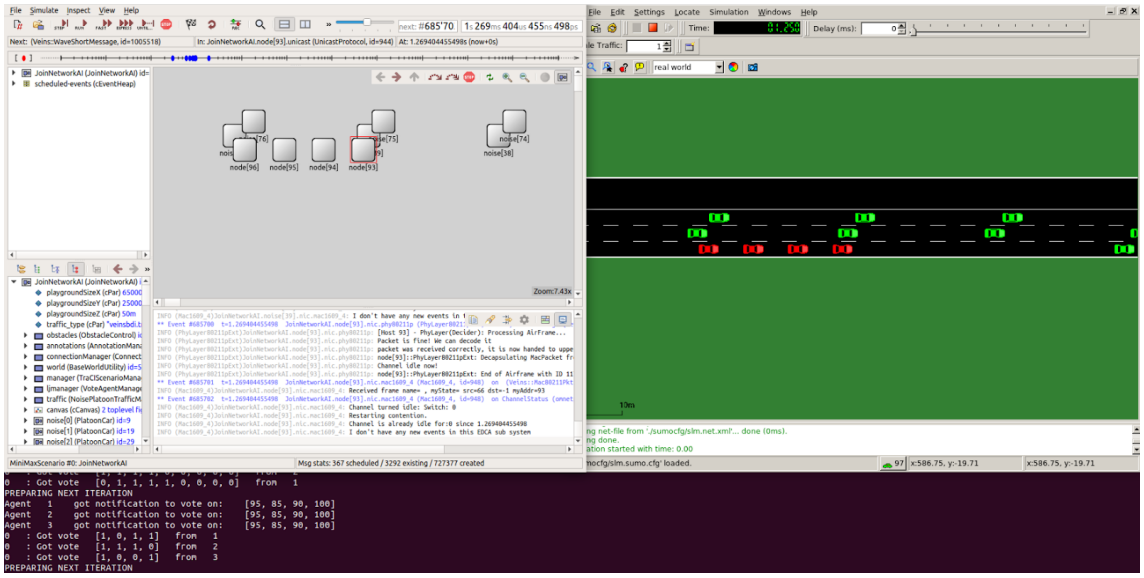


Figure 4.2: Simulation framework GUI. The network information of OMNeT++ is displayed on the top-left window, the SUMO traffic environment in the top-right window and the agents actions in LightJason are displayed as terminal output in the bottom window.

posed simulator works on extending already existing integration of SUMO and OMNeT++ (i.e. the VEINs framework [SGD11]) in order to add the capability to endow vehicles with high-level decision-making capabilities using MAS. To work with a MAS environment, the network simulator establishes a connection to a **LightJason** [AKM16] server, a BDI-based multi-agent framework. LightJason provides the high-level decision-making aspect of the simulation, such as deliberating on what maneuvers to perform using a concurrent architecture. Moreover, due to its simplicity of the agent's reasoning cycle, high-modular and scalable design it is easy to maintain and to integrate with other systems. The Graphical User Interface (GUI) of the integrated simulation platform is given in Figure 4.2.

A typical communication process between all three simulators is presented in Figure 4.3. The OMNeT++ component of the simulation framework acts as client that establishes a connection to both SUMO (facilitated by extending the VEINs framework) and LightJason components (using a socket connection), both acting as servers. During this initialization phase, the OMNeT++ Connection Manager (OCM) will request SUMO to create new vehicles and assign them a unique identifier. This identifier is then sent over in an agent creation request to LightJason. The OCM uses this identifier to delegate decisions to the correct vehicle application and send triggers to the vehicles associated agents.

Control of the simulators timestep is given to OMNeT++, with the communication with SUMO being handled by the VEINs framework. Information about the environment (e.g. current speed and location) is sent over to the vehicle controllers. In the opposite direction, the vehicle controllers send low level instructions to the vehicles in the traffic simulator to perform any maneuvering needed. These maneuvers can either be triggered from the vehicle controllers (e.g. a vehicle following the instructions of a car-following model attempting to maintain a certain distance from the lead vehicle) or as a decision from the vehicles corresponding agent.

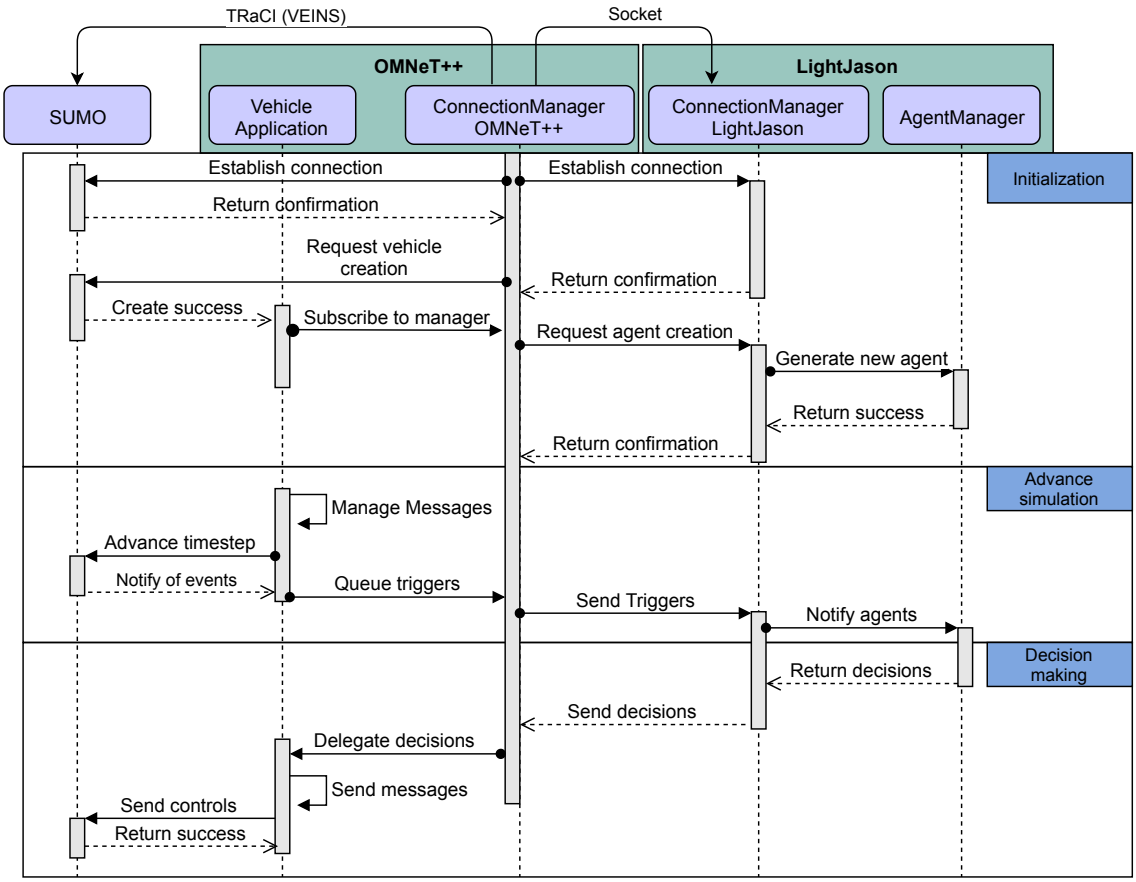
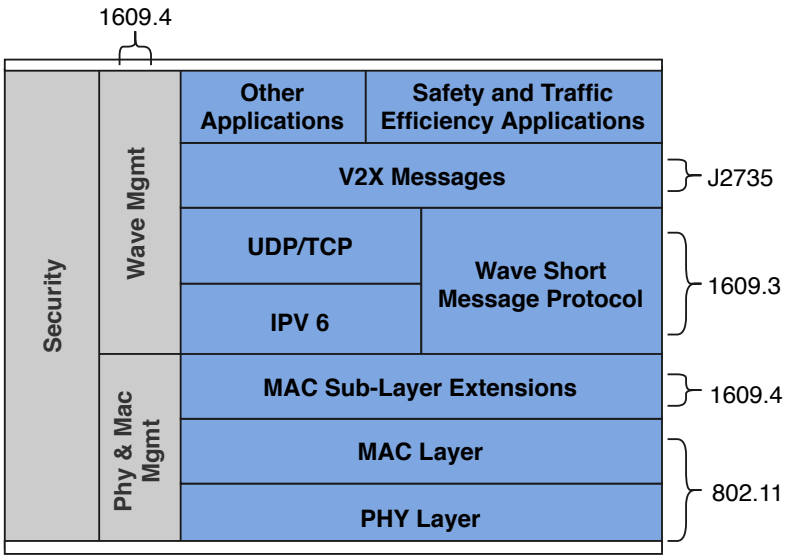


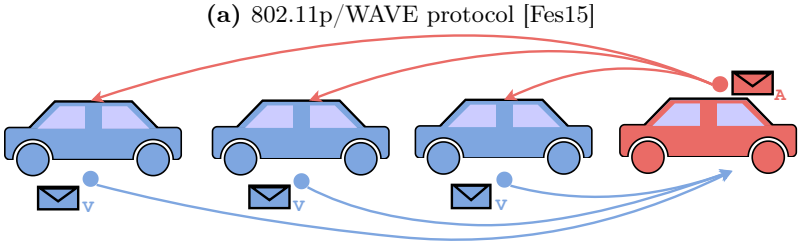
Figure 4.3: Sequence diagram of the simulation framework.

Whenever the vehicle controller wishes to notify its agent of an event (e.g. receipt of a message or detection of obstacle), the controller creates a trigger and the connection manager queues the trigger to be sent in the next timestep to the LightJason component. The LightJason server receives all triggers at the end of a given timestep and delegates them to their corresponding agents, waking them up in the process. The agents then deliberate upon these triggers and reach decisions that are sent back over to their corresponding vehicle controllers in OMNeT++. The agents go to sleep when all decisions are made in order to free processing time. The vehicle controllers then perform the instructions sent by their agent, which can be either sending a message to another vehicle or the conversion of a high-level maneuver to a lower-lever maneuvers (e.g. convert a JOIN platoon maneuver to a sequence of lateral and longitudinal controls).

In the following, we present an illustrative example use case (vehicle crash) of the interactions between the different components of the simulation framework. When a vehicle crash occurs in the microscopic traffic simulator (SUMO), an event is sent to the associated vehicle application. In such a scenario, the vehicle application would immediately start broadcasting information through wireless communications to alert other vehicles making use of the OMNeT++ network simulator. Vehicles that receive this message would send a trigger to their LightJason agent in order to receive instructions on how to proceed based on their current goals and state.



(a) 802.11p/WAVE protocol [Fes15]



(b) Network diagram example of a voting exchange

Figure 4.4: Network simulation protocols and networking

4.3.3 Message Exchange Between Vehicles

Coordination mechanisms often require the timely and reliable exchange of relevant information between vehicles, which can be enabled by selected wireless networks. In vehicular networks vehicles most often exchange messages using the wireless ad hoc 802.11 p/WAVE protocol (ITS G5 protocol in Europe) that has been specifically designed for vehicular environments. Ad-hoc networks allow reducing the latency to a minimum through device-to-device (D2D) communications and by keeping local information (i.e. platoon information) within a contained geographical area. The 802.11 p protocol stack is depicted in Figure 4.4a. Vehicular networks have a very dynamic network topology due to the mobility of the vehicles, the challenging propagation environment, among others, leading to frequent disconnections between nodes (e.g. see [HL08]). An example of this type of network topology is depicted in figure 4.4b, where a platoon leader sends a message A, containing voting information, to its followers. To which the followers reply with votes V to the platoon leader. Current or future cellular networks (e.g. LTE [ACC+13], 5G [CHS+17]) will be able to support selected ITS applications.

Whenever an agent wishes to transmit information to another, it passes the information over to its associated controller in the OMNeT++ simulator in order to perform the necessary message handling. Message transmission occurs via broadcast using dedicated messages for negotiation similar to the protocols developed in [SDC15] and [SBJ+14]. Instead

of piggybacking acknowledgments in the CAMs, dedicated broadcast messages are used. Potential alternatives, however, could be receiver-based approaches [GHMK16], however the assessment of the most effective method for reliable message exchange is outside the scope of this work.

Table 4.2: Coordination message meta-data

Field	**Type**	**Role**
Message Id	Integer	Message identifier
Recipients	Sequence	Intended recipients.
Type Id	Integer	Message type. E.g. *ACK*, *VOTE*, etc.
Sender Id	Integer	The ID of the sender of a message.

The OMNeT++ simulator provides tools to facilitate the definitions of messages. In the case of agent-based coordination a base message type is defined (see Table 4.2) from which a more concrete message can be implemented. Each message intended for coordination purposes will have a list of all intended recipients, a randomly generated message identifier and a type identifier. Every vehicle maintains a cache of each message that is sent and received in order to keep track of the current status. After a given timeout, the cache is checked for any vehicles that have not replied yet. If at least one vehicle has not confirmed receipt, the message stored in cache is re-sent, albeit with the recipients list reduced to only those remaining.

Table 4.3: Example of a message implementation

NOTIFY_ELECTION		
Field	**Type**	**Description**
Election Id	Integer	The identifier of the election
Candidates	Sequence	The candidates that can be voted on
Context	Integer	The context of the election. E.g. speed or route
Context Args	Sequence	Optional arguments

Specific coordination messages (e.g. a vote message) include all of the meta-data described above. Vehicles differentiate message types by the message type identifier field (table 4.2). This field holds an unsigned integer indicating to the agent what type of message was received. Any type of coordination messages extends this base message and defines new the proper message types in order to ensure proper handling of messages by the vehicular application. For example, a *NOTIFY_ELECTION* message, which is used to announce a new election, extends the base negotiation message to add the Electiond Id, Candidates, Context and Context Args fields (see table 4.3) in order to allow an election manager to properly inform the voting agents of the election type and context.

4.3.4 Belief, Desire and Intention Behaviour

The high-level decision-making is modelled in the LightJason MAS component. In this simulator, agent behaviour is specified using Agent speak language (ASL)[3] files and its actions with the environment are defined as Java methods. In order to exemplify the agent behaviour modelling, a simple routing experiment is described in this section, with the primary goal of verifying that the decision-making agents can receive environment state from OMNeT++ and deliberate on what actions to perform accordingly.

The routing example consists of a road network that starts at an origin site n_0 and ends at the destination site n_7. A vehicle is injected into the traffic network and an agent is associated to that vehicle. This vehicle agent has the desire to reach the destination site n_7 starting from site n_0. The agent holds in its belief base, all the existing links in the network (including knowledge on whether these links are available to travel by) and the current route being taken. In the experiment configuration file, any link within the network can be closed. When a link within the vehicles current route is closed, the agent must construct an alternative path based on its knowledge of the environment. Whenever the vehicle controller detects that a link is closed, it must notify its agents using triggers. Triggers are defined in the ASL file and execute plans. A sample script for the routing behaviour, with beliefs and plan definition, is given in Listing 4.1.

Listing 4.1: Simple ASL script for an agent to re-route

```
//Belief definitions
//connections between nodes in the route and their state
//0 == closed, 1 == opened
link('n0', 'n1', 1).
link('n1', 'n2', 1).
link('n1', 'n3', 1).
link('n2', 'n5', 1).
link('n3', 'n6', 1).
link('n3', 'n4', 1).
link('n5', 'n7', 1).
link('n6', 'n7', 1).
//The current route
currentRoute(['n0','n1','n3','n6','n7']).
//have we reached the target? 0 == no, 1 == yes
reachedDestination(0).
//Call the entry point plan
!main.

//Definition of rules
//Find a new route
findroute(Target, Route) :-
    Route = collection/list/create(Target);
    $setnodes(Target, Route).
setnodes(Origin, Route)
    :- >>(link(N1,N2,1), N1 == Origin);
    collection/list/add(N2, Route);
    $setnodes(N2, Route)
    :- ~>>(link(N1,N2,1), Origin == N1).

//Plan definition
//Entry point plan, send the first destination to the controller
+!main : >>currentRoute(L) <-
```

[3]Files written using either the Agent Speak or Agent Speak++ declarative languages

```
    generic/print("Router agent started").
//Trigger that a node has been reached
+!reached/node(S, L) : S > 0 <-
    [N|NL] = L;
    -currentRoute(L);
    +currentRoute(NL);
    generic/print("Remaining route:", NL)
        : S == 0 <-
    generic/print("No more future nodes in path").
//A link that we wanted to cross is closed
+!link/closed(N1, N2) <-
    -link(N1, N2, _);
    +link(N1, N2, 0);
    $findroute('n0',R);
    -currentRoute(_);
    +currentRoute(R);
    send/route(R).
```

4.4 Modelling Social Coordination in Connected Automated Vehicle Settings

Recently the concept of CAV has gained momentum [KB05]. A notable example of cooperative driving of CAVs is *platooning*, where a group of vehicles follows a leading vehicle controlling longitudinal and lateral control using local sensor information and information exchanged through V2V communications. In such an application the proper control of the vehicles is subject to constraints in both the kinematics and the communication latency. As such proper simulation tools need to account for these factors. Many case studies in cooperative traffic scenarios are focused on platooning, intersection management and/or lane merging. To validate the proposed simulation framework, two types of collective decision-making strategies are conceptualized and implemented: (i) Bargain-based negotiation mechanism applied to lane merging and (ii) Voting mechanism applied to platooning. Other collective decision-making mechanisms (i.e. auction-based) can be considered as the proposed framework is flexible to accommodate their implementation. However, their implementation and the comparison with the voting mechanisms is outside the scope of the chapter.

4.4.1 Bargain Mechanisms

In the bargain mechanism vehicular interactions occur between a pair of vehicles, characterized by the tuple $< V_b, V_s >$, where V_b is a vehicle that wishes to perform a lane change maneuver onto a lane that is currently occupied by vehicle V_s. In order for V_s to create a space to allow V_b to merge into its lane, V_b must send a monetary offer m, which represents the payout that V_b will give to V_s in compensation for creating a gap to merge onto the lane.

An initial offering m_i is obtained by sending a trigger to the agent associated to V_b, which sends back a decision with the value of m_i, a message with this value is sent over to V_s who triggers its own associated agent to deliberate on the value of the offer and decide if it should be rejected or accepted. In case of rejection V_b will continuously request another offer $m_k > m_i$ from its agent and send it back to V_s until the offer is accepted. When the offer is accepted, V_s will notify V_b that it is allowed to merge, in which case a lane change maneuver is performed. This simple bargain protocol includes all the simulation framework components, in form of (i) realistic messages exchange in OMNeT++, (ii) deliberation on payouts in LightJason and (iii) vehicle kinematics and its interactions simulated in SUMO.

4.4.2 Voting Mechanisms

Voting is social choice mechanism that is widely used in multi-agent systems as consensus and coordination strategy [PKSA06]. The voting strategy can be seen as mechanism where agents input **preferences** and the output of each is adopted as a decision or a solution by all of the agents. A desirable voting mechanism would be one that can pool together the various preferences of the agents and reach a decision that best reflects the interests of the group as a whole.

In general, a voting procedure starts with all the members that are enfranchised[4] coming together to have a meeting that is initiated by a *chair*. Any member can propose a motion and is debated among all members of the committee. The *chair* then calls all members to cast votes either in favor or against the proposed motion which is carried or not according to the voting rules of the committee [PKSA06].

Let $N = [n]$ be the set of *voters* participating in coordination tasks, A be the set of m *alternatives*, $\{a_1, ..., a_m\}$, and V be the list of votes over A, $\{v_1, ..., v_n\}$. A tuple (A, V) is the election ε. Each voter i has an utility function u_i for alternative a, which is translated into a vote. Each voter is represented by the vote that specifies its preferences over the alternatives in A.

4.4.2.1 Voting Rules

Within every election, all members must agree upon a voting rule that determines how members cast their votes and how winners are determined. Formally, a voting mechanism is a rule that given a profile ε determines the winner, which can be represented by a social choice correspondence function:

$$F : \{\varepsilon = (A, V) | V \text{ is a preference profile } \} \rightarrow P(A)$$

where $P(A)$ is the power set of A. For any election ε, $F(\varepsilon) \subseteq A$, corresponds to the set of the election winners. In case of multiple winners, a tie-breaking rule is applied.

[4] Agents with the right to vote and an entitlement to a fair outcome.

For single candidate elections that is a single choice out of many, the following four voting rules are used [ASS02]:

- *Plurality*: A voter states its preferred candidate, and the winner is the candidate who scores the highest among its competitors.

- *Approval*: Each voter selects a set of favourite candidates. The winner is the candidate with the highest number of approvals.

- *Borda*: Each voter ranks each candidate according to their preferences and attributes a score to each one. For a candidate set of size m, voters give $m - n$ points to the nth ranked candidate (e.g. $m - 1$ to their first choice, $m - 2$ to their second, ..., 0 to their least approved). The winner is the candidate with the most points.

- *Copeland*: Uses a round-robin style election, where each voter casts their preference on every possible pairwise candidate set. The winner is the candidate with the most pairwise wins.

When we need to select more than one candidate we apply a *committee election* voting rule that selects a set candidates of k size. Such elections are defined as a tuple (C, V, k) with $k \leq |C|$. **Minimax Approval** and **Minisum Approval** are the two voting rules typically used. In both cases, votes are cast as an *approval vector*. Minisum rule selects a committee (i.e. a set of winners) for which the sum of a given metric function between all votes and the committee is minimal. Minimax rule selects a committee for which the maximum a given metric function between a vote and the committee is minimal [BDR15].

As metric function, we resort to the widely used Hamming distance H [DM16] that measures the number of positions between two strings of equal length where the symbols differ. For instance, consider two agents a_1 and a_2, with preferred routes r_1 and r_2 respectively and a node map represented by a list of nodes $M = [M_1, M_2, M_3, M_4]$. The preferred route of each agent is a vector in $\{0, 1\}^{|M|}$ which has at position i a "1" if the agent wishes to visit node M_i or a "0" if the agent does not want to visit M_i. Let $r1 = [0, 1, 1, 0]$ and $r2 = [1, 0, 1, 0]$, the hamming distance H between $r1$ and $r2$ would be 2, as different symbols can be found in positions 0 and 1 of $r1$ and $r2$.

4.4.2.2 Voting on Platoon Properties

Voting is used to allow a platoon of vehicles to achieve a consensus on the average cruising speed and the route to take to reach a shared destination. For the speed voting an iterative process [MPRJ17] is used, while a single round process is used for the route vote. Herein, we consider a sequential decision-making process on two platoon properties (speed, route), i.e. first vehicles reach a consensus on the route and then vote for the speed, as follows:

- **Route:** the voting phase on route follows only one iteration, as similar works using committee election in vehicular applications implemented iterative elections by having dissatisfied elements leave the voting group [DM16]. Given that such iterative process is not possible (i.e. the goal is to maximize platoon stability), only one iteration is performed. The candidate set used in route voting is a vector C_r containing

all the nodes a vehicle agent may vote one.

- **Speed:** the list of speed candidates is generated as an ordered vector $C_v \in \mathbb{N}_{>0}$. After each voting iteration k, the top scoring half of the iteration's candidate vector (C_v^k), are used as the candidates of the following $k+1$ iteration. As such $|C_v^{k+1}| = \frac{1}{2}|C_v^k|$. The speed voting phase is over and the speed is set when $|C_v| \leq 3$.

After receiving the notification of the election, all elements in N will begin to construct their voting sequence over the candidate sequence C_m, A_m, according to the defined voting rule, the context m and any other contextual information that was sent by the chair.

Before beginning to construct A_m, agents must evaluate the utility of each candidate in order to correctly place their votes. The perceived utility of each candidate $c \in C_m$ is measured using the normalized Gaussian radial basis function based on [San13], detailed in equation (1). Let M the set of possible contexts for coordination (e.g. coordinate on what speed to travel at). The utility function outputs a value between 0 and 1 for a given consensus subject $m \in M$ based on the agents preference P_m and its tolerance to deviations T_m for subject m. The input x_m is information regarding the candidate the agent is evaluating.

$$U_m(x_m) = e^{-\frac{(x_m - P_m)^2}{T_m}} \tag{4.1}$$

In scenarios where consensus must be reached on multiple subjects (e.g. speed and route), the total utility U_t for a given agent is obtained as the weighted sum between all measures of utility. These utility functions are formally described as follows, where w_i is the weight given to each measure of utility and U_{mi} is the measured utility of the ith coordination context. For the scope of this current, all measures of utility are weighted equally.

$$U_t = \sum w_i \cdot U_{mi} \tag{4.2}$$

In the following we setup two simulation scenarios as case studies: a lane-merging, and a deliberation to reach consensus over platoon properties. In the former, we discuss the execution performance of the proposed simulation framework as the number of agents and communication rates increase. In the latter, we showcase and benchmark well-known single-candidate and committee election voting rules to show the feasibility of the proposed simulation framework.

4.5 Results and Discussion

The case studies theoretically described in Section 4.4 were implemented in the simulation framework presented in Section 4.3 with the following key objectives:

- study the performance of the simulation framework in Section 4.5.2 resorting to the lane-merging scenario presented in Section 4.4.1.

- demonstrate its applicability to the validation of potential MAS solutions to CAVs in Section 4.5.3. A platoon voting scenario (Section 4.4.2) is used to exemplify and test a potential real-world use case.

4.5.1 Settings

The parameter setting for the simulation framework is the same for both scenarios, except where noted otherwise. The simulation framework requires the definition of parameter sets for all three simulation components, namely network simulation, microscopic traffic simulation and MAS framework, which are provided in the following.

Network Simulation: The main parameters of the OMNeT++ network simulator are given in Table 4.4. The two-ray interference model [SD11] is used to model the signal strength as a function of the distance (i.e model the wireless propagation channel). Small-scale fading is modelled using Nakagami-m fading with a value of m varying as a function of distance d [IHO+13]. We resort to the 802.11 p/WAVE protocols implemented in OMNeT++. CAM/beacon messages are broadcasted with a frequency of 10 Hz. Additional important parameters are presented in Table 4.4, while the simulation also relies on other default parameters of OMNeT++.

Traffic Simulation: The main parameters for the traffic environment are given in Table 4.5 and are shared by both simulation scenarios, with the exception of the car following model. The lane merge scenario utilizes an adaptive cruise control (ACC) car following model, while the platoon voting scenario employs Cooperative ACC (CACC). Both models are already included in SUMO/PLEXE.

MAS framework: The parameter set for the MAS framework is related to the agent's preference and tolerances (e.g. each agent has a defined tolerance for a given decision). The preferences and tolerance of each agent is drawn from a normal distribution and is dependent on the decision to be taken (e.g. vehicle speed).

Scenario dependent parameters: Parameters that are scenario specific include the road characteristics, background traffic density, the number of cooperative vehicles and the cruise controller scenario. Table 4.6 presents a summary of these parameters. Note that the bargaining scenario does not include any background traffic, since all vehicles are actively cooperating.

Table 4.4: Main Network simulator (OMNeT++) parameters

Parameter	Value
Wirelesses propagation model	Two-ray interference
Fading model	Nakagami-m fading
Transmission Power	15 dBm
Bit rate	6 Mbps
Antenna height	1.895 m
PHY model	IEEE 802.11p
MAC model	1609.4 single channel (CCH)
Frequency	5.89 GHz
Access category	AC_VI
MSDU size	200 B

Table 4.5: Main Microscopic Traffic Simulation (SUMO) parameters

Traffic Simulation	
Car Following Model	Krauss, ACC and CACC [SJB+14]
Lane Change Model	LC2013 (SUMO default)
Maximum Vehicle Speed	100 km/h
Maximum vehicle acceleration	2.6 m/s^2
Vehicle Length	4 m
Vehicle Controllers	
Engine lag	0.5 s
Weighting factor	0.5
Controller bandwidth	0.2 Hz
Damping factor	1
Desired gap length	5 m
Headway time	0.3 s - 1.2 s
ACC parameter δ	0.1
Distance gain	0.7
Speed gain	1.0

Table 4.6: Scenario-specific parameters

	Scenario	
Parameter	**Bargaining**	**Voting**
Road Type & Length (km)	Highway - 10 km	Highway - 10 km
Lane Count (#)	8	3
Background Traffic (veh/km)	N/A	100-300
Cooperative Vehicles	100-1000	4-8 (platoon length)
Cruise Controller	ACC	CACC

4.5.2 Simulation Framework Validation: Lane-Changing Case Study

In order to study the performance of the simulation framework, we resorted to a lane-merging scenario where a bargain strategy is applied for negotiation between vehicles (see Section 4.4.1 for additional details). Note that vehicle generation ensures that no collisions will occur between vehicles and that no gap-creation control algorithm is required. The vehicle count starts with 100 vehicles and increments in steps of 100 up to a maximum of 1000 vehicles. Half of those vehicles will attempt to merge into a lane, while the other half will negotiate a price to allow merging. In this study we consider the following metrics:

- **Processing time** t_p (ms) – time interval between the start and the end of a given timestep. This metric is presented separately for each component of the proposed simulation framework.

- **Execution time** t_e (s) – time interval between the start and the conclusion of one simulation run.

- **Queued Triggers** QT (#) – number of triggers that are queued by the vehicle applications to be sent over to the LightJason agents during one timestep.

All experiments were performed resorting to a Linux machine with an i7-4770K CPU with a clock speed of 3.50 GHz and 12 GB of memory.

4.5.2.1 Lane-Changing Use Case: Results

The processing time for each framework component is depicted in Figure 4.5. These results show that both SUMO and LightJason (Figures 4.5a and 4.5b respectively) show linear time complexity for an increasing number of nodes; SUMO presents better performance than LightJason in terms of lower processing time. The processing time of OMNeT++ (Figure 4.5c) increases exponentially with the number of simulated vehicles and is the highest of all components. These results are expected since OMNeT++ performs more complex operations for simulating vehicular networks (e.g. calculations between all pairs of vehicles) when compared with other components. The full processing time of one timestep (figure 4.5d) is in a worst case scenario slightly below 600 ms being mostly influenced by OMNeT++'s processing time.

Figure 4.6 presents the total execution time of a simulation run for different number of simulated vehicles. Note that the simulation time is 3 s. As expected, the execution time grows exponentially with the number of vehicles being simulated. For instance, in the worst cases scenario (i.e. scenario with 1000 vehicles) the execution time is 6 minutes for each 1 second of simulated time. The execution time can be greatly reduced if improvements (e.g. see [FF12]) are made specially to the network simulator component.

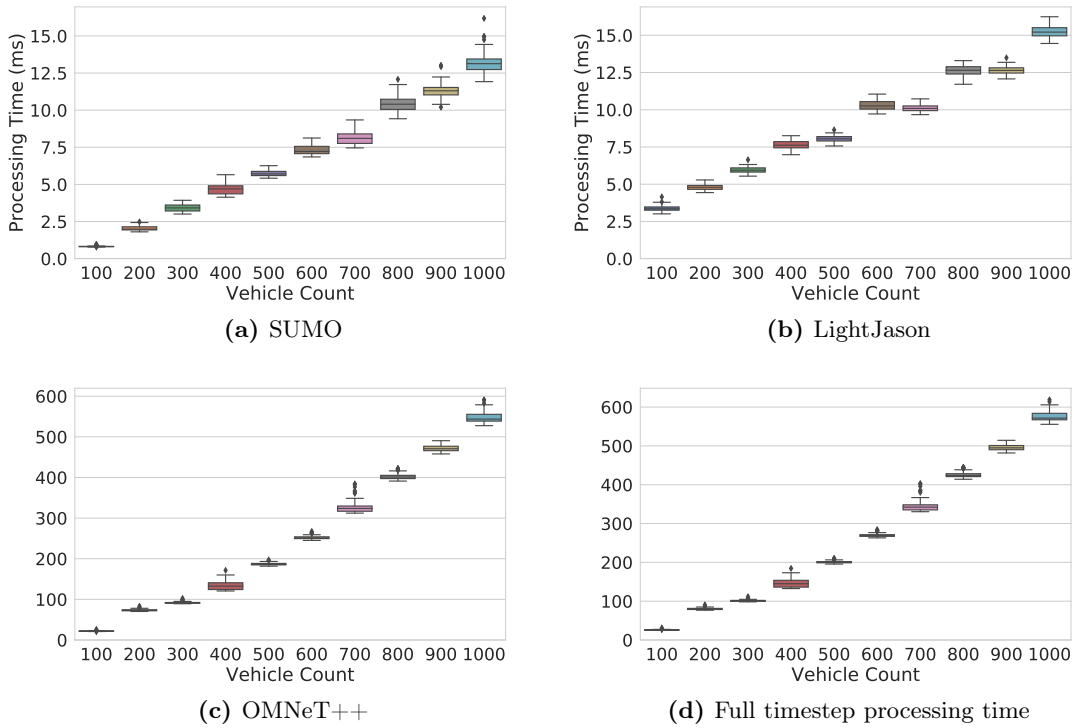


Figure 4.5: Processing time of one timestep per framework component

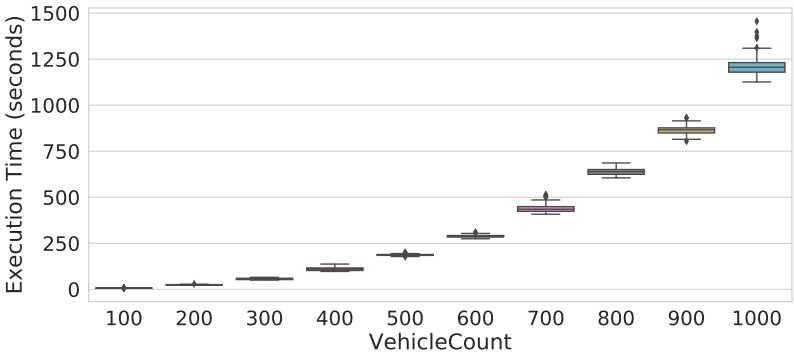


Figure 4.6: Total execution time of a simulation run

An analysis of the processing time of the LightJason component in regards to both the agent vehicle count and the number of triggers to be sent is presented in figure 4.7. The processing time shows high correlation with the number of queued agents and less with the number of agents actually instantiated. This is to be expected as only the agents that are triggered are woken up and perform their actions. However, a slight increase with agent count is still present, this could potentially be due to poor collision handling within the data structures responsible for agent management, and is grounds for further optimization.

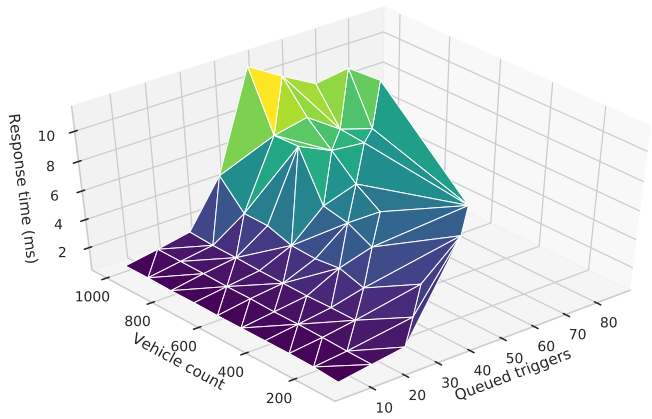


Figure 4.7: Queued triggers and response time according to vehicle count

4.5.3 Social Coordination in Connected Automated Vehicles Platoon Formations: Application of Voting Schemes

The platooning scenario serves as a potential use case concept to analyze the feasibility of implementing coordination mechanisms for CAVs in the proposed framework. The case study of this section is based on the platooning voting scenario presented in [TdK18] and has the objective of gathering information on both communication complexity and agent satisfaction in terms of social welfare functions. The platoon cruising scenario starts when an external trigger (e.g. initial platoon formation) forces the platoon to coordinate among themselves to set the **average cruising speed** and the **route to take** while the formation is maintained. Four common single candidate voting rules are used to set the speed: Approval, Borda, Copeland and Plurality; and two committee rules are used to select the route: Minisum and Minimax, as detailed in Section 4.4.2. A visual representation of this scenario is given in Figure 4.8.

Each run is setup according to the the vehicle density, platoon size, single voting rule and committee voting rule. The platoon size starts with a size of 4 and increments in steps of 1 up to a maximum of 8 elements. The vehicles density can either be [100, 200, 300] veh/km. Every simulation run is repeated 100 times.

In this platoon cruising scenario the performance of each voting rule on both communication and welfare is evaluated, in order to gain insight on the viability of the mechanisms for real-world deployment. Data regarding both the **communication complexity** and **agent satisfaction** is collected. The simulation variables and parameters are defined as follows:

- **Vehicle density** – amount of vehicles in a one km stretch of road.
- **Platoon size** – number of elements in a platoon.

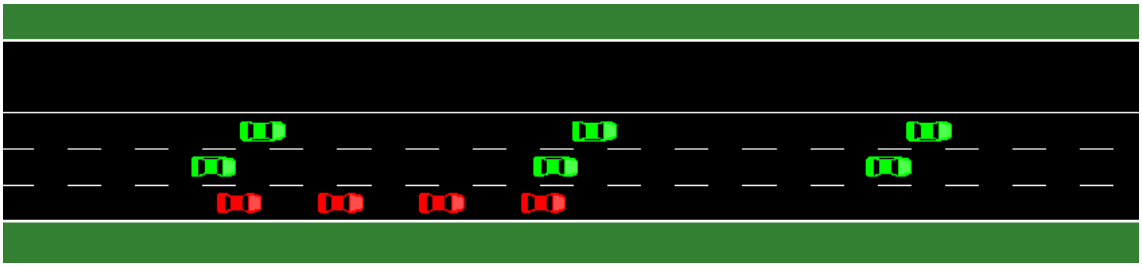


Figure 4.8: Voting scenario extracted from SUMO microscopic traffic simulator. Vehicles performing platooning colored in red, while background vehicles are depicted in green.

- **Preferred Speed** – preferred average travel speed of a vehicle agent.
- **Preferred Route** – The preferred route a single agent wishes to take.
- **Single voting rule** – The single candidate election voting rule used during the cruising speed election.
- **Committee voting rule** – The committee election voting rule used during the route election.

The following metrics are considered to evaluate the use case in terms of user satisfaction (i.e. utilities) and in terms of network performance (i.e. channel busy ratio):

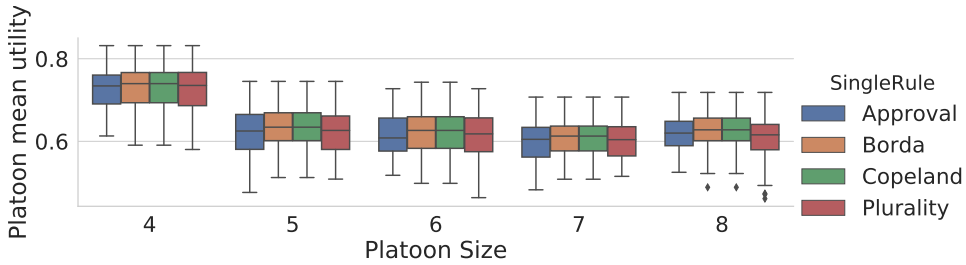
- **Utility on Speed** U_s – agent's perceived satisfaction on the chosen cruising speed after the conclusion of an election.
- **Utility on route** U_r – agent's perceived satisfaction on the chosen route after the conclusion of an election.
- **Channel Busy Ratio** CBR – ratio of time during which the communication channel is busy.

The Processing time t_p and Queued Triggers QT metrics (defined in Section 5.2) are again considered to evaluate the performance of the simulation framework.

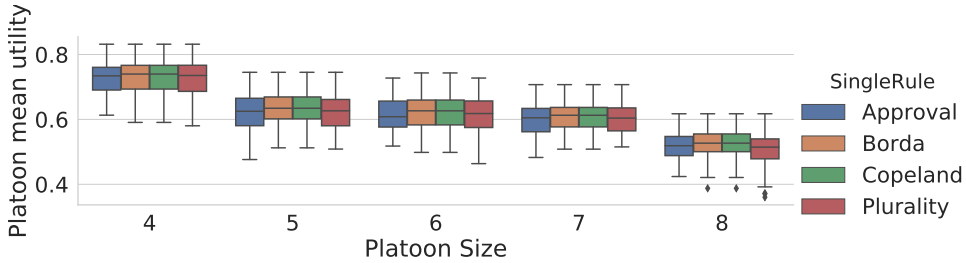
4.5.3.1 Results

We assess the viability of voting mechanisms for coordination of platoon formations in terms of communication complexity and agent satisfaction. We further evaluate the performance of the simulation platform in this more challenging scenario.

Agent Welfare: The welfare of the platoon, from an utilitarian perspective, are illustrated in figure 4.9. Figure 4.9a compares the mean platoon welfare between each single candidate voting rule when using the Minisum voting rule, while figure 4.9b performs the comparison when using the Minimax rule instead. Although both committee rules behave very similarly at small platoon sizes, the Minimax rule loses to the Minisum rule when the



(a) Minisum



(b) Minimax

Figure 4.9: Analysis of each voting rule on the utilitarian welfare of the platoon

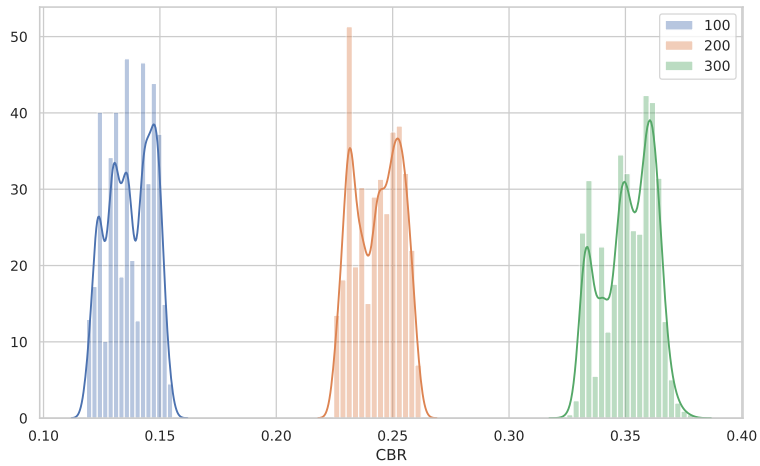
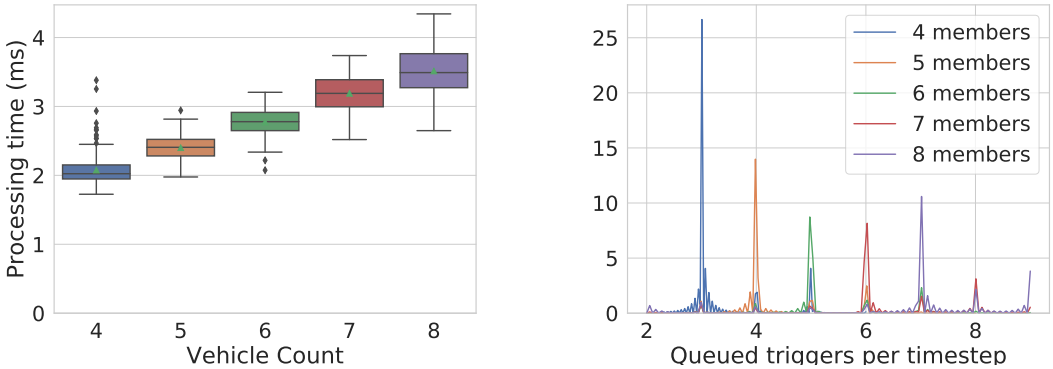


Figure 4.10: CBR distribution by vehicular density

voting committee increases. In regards to the single voting rules, results are very similar, with the Borda and Copeland having near equal mean utility and performing better than the Plurality and Approval rules.

Communication complexity: The Channel Busy Ratio (CBR) was measured for all nodes in the simulation for varying vehicular densities. The results presented in Figure 4.10 show the expected behaviour of increased CBR with increasing vehicular density as show in [SGHH11]. With a density of 100 veh/km the channel tend to be busy between 13% to 15% of time, with a density of 200 veh/km this value jumps to an interval between 23% and 26% and with the highest density of 300 veh/km CBR values vary between approximately 32% and 37%. The results show the viability of using the simulation framework to perform



(a) LightJason processing time by platoon size

(b) Distribution of triggers by platoon size

Figure 4.11: Analysis of the interaction with the LightJason agents

validation on the communication protocol implemented by decision-making mechanisms in a variety of scenarios.

System performance: Figure 4.11a depicts the processing time of the LightJason agents for an increasing size of the platoon. The results show that the voting algorithms, with the evaluated input size, scales linearly in time complexity with an increasing platoon member count. A potential exponential growth could be masked behind a small input size, however it is not expected for this voting application to be utilized with higher orders of magnitude in input size. The increased response time can also be due to the higher amounts of triggers to be processed, which increases with platoon size as illustrated in Figure 4.11b.

4.6 Summary

In this chapter a simulation framework to validate and analyze MAS-based coordination mechanisms for vehicular networks is presented. The framework in question had the requirements of providing a vehicular traffic simulator framework that allowed for near real-world modelling of constraints within vehicular networks (both at the kinematic and network level) and endow each vehicle with high-level decision-making cognitive capabilities, with the use of BDI-based agent modelling. To assess voting as a mechanism to achieve social coordination in autonomous vehicle applications, we considered a scenario to allow a platoon to decide on cruising speed and travel route, analyzing the fitness of a voting mechanism on the platoon's welfare and the impact on the communication medium. We studied the viability of four commonly used voting mechanisms namely, plurality, Borda, Copeland, and approval, to enable coordination in a platooning scenario considering an unreliable communication channel. The results indicate these social consensus mechanisms show good results in maintaining high satisfaction, as measured by the social welfare functions, and such mechanism are a good fit for autonomous vehicles coordination. Furthermore, voting mechanisms have an acceptable response time for low platoon sizes (i.e. < 9), but larger platoons might need additional methods to timely achieve consensus.

To further assess and validate the integrated framework we performed a benchmark using a lane-merge scenario using a bargain negotiation. The obtained results shows that framework scales well up to a 1000 vehicles with room for improvement.

Due to its flexibility, the simulation framework can be used to evaluate other potential coordination mechanisms (i.e auctions). However, the comparison of the voting with other methods is considered outside the scope of the chapter.

Chapter 5

Auction-Based Incentives for Social Coordination in Platoons of Autonomous Vehicles

5.1 Introduction

Autonomous driving has gained momentum in recent years due to impressive technological advances put forward by both academic and industrial companies. Currently, automotive manufacturers and tier 1 suppliers are designing, building and testing automated vehicles that navigate in complex scenarios without explicit cooperation with human drivers or other vehicles [ZBSea14]. In parallel, advances in vehicular networks have enabled explicit cooperation between vehicles using vehicle-to-vehicle communications (V2V) and between vehicles and infrastructure using vehicle-to-infrastructure (V2I) communications. In this context, cooperation is established from the event-driven or periodic exchange of static and dynamic data (e.g. location, trajectories) e.g. through Cooperative Awareness Messages (CAM) [Bd16].

Only more recently the concept of Connected Automated Vehicles (CAV) has gained prominence [KB05]. A notable example of cooperative driving of CAVs is *platooning*, where a group of vehicles follows a leading vehicle controlling longitudinal and lateral position using local sensor information and information exchanged through V2V communications. Platooning is seen as a promising approach to reducing road congestion and improving safety [JLW+16]. Besides the dynamic control of vehicles, the formed string needs to agree on several tactical and strategic decision-making aspects[1] in the different stages, namely i) formation (e.g. based on vehicle destination), ii) joining of new vehicle (e.g. decision on target speed), ii) merging, iv) dissolution, among others.

Multi-Agent Systems (MAS) have been proposed to model different traffic applications [RL05, MRCK14]. Moreover MAS research has devised various collective decision-making mechanisms (e.g. auctions, negotiation, voting) to reach consensus over the agents' aggregated preferences. Within vehicular applications, voting mechanisms have been used in platooning [TdK18] and leader election [Fer12], whereas auction-based approaches have been also studied for vehicular coordination, namely for intersection management [CBS13], trajectory coordination [RS16], and road network reservation [DLDS13]. Nevertheless, there is a lack of research studying mechanisms for vehicular cooperation i) at a *tactical*

[1] Vehicular decision-making levels have been classified by Hollnagel et al.[HNL04] into strategic (e.g. route), tactical (e.g. maneuvering) and operational (e.g. vehicle control).

level that takes into account individual driver preferences and ii) *realistically assessing the performance* of the decision-making mechanisms in cooperative traffic scenarios. The performed experiments do not usually account for a wide spectrum of constraints that CAVs will face in real-world deployments.

In this chapter, we argue that MAS mechanisms can achieve consensus in collective decision-making for CAVs under realistic settings and constraints (e.g. unreliable communication channel). We suggest auction-based mechanisms as coordination approach for the have the property of incentivising fair bidding while discouraging malevolent actions. The main contributions of this chapter can be summarized as follows:

1. We propose to consider different auction rules together as a means of collective decision-making for social coordination of autonomous vehicles in platoon formation;

2. We use the simulation framework proposed in chapter 4 to analyze the effect of auction mechanisms on the platoon formation and on the social welfare performance metrics from the perspective of the whole system

The remainder of this chapter is organized as follows. In Section 5.2, we review the relevant work on social consensus mechanisms for vehicle coordination. In the following sections 5.3 and 5.4, we present the coordination concepts of how to apply auction-based mechanisms to achieve joint consensus. Section 5.4.3 details the application of these mechanisms in a vehicle platooning scenario. The realistic evaluation of the auctions for vehicular coordination is given in Section 5.5.1. Section 5.6 summarises the main topics of this chapter.

5.2 Related Work

Although there is already a significant amount of literature concerning both platooning and autonomous vehicles within the field of ITS, as well as their interactions, most efforts focus mainly on control and communication aspects [LK13, JN16, PSKM+18].

In this chapter we study the use of market-based approaches for vehicular cooperation at a tactical level that take into account vehicle's preferences and realistically assess the performance of the deliberation process in cooperative traffic scenarios. The use of market-based approaches have been proposed for solving resource allocation problems in cooperative traffic management systems. Auctions have been used as coordination mechanisms for intersection management, either as reservation mechanism among vehicles or traffic signal controllers, as reported in [VO12b, RMS15]. Rewald et al. [RS16] explore the use of auction-based control to achieve cooperative behavior among autonomous vehicles, while taking into account the personal objectives and preferences of the auction participants. Domingues et al. [DCM+18] consider a bargain negotiation protocol in a lane-merging platoon application. An auction system for platoon freight scheduling is developed in [KMR+16], which is modeled as an assignment and optimization problem and solved using auctions.

Other collective decision-making processes based on the computational social choice approaches have been applied to vehicular coordination at a tactical level. Dennisen et al. [DM15] proposed an agent-based voting architecture for traffic applications and theorized possible applications for taxi-sharing and platooning scenarios. In [TdK18] a comparison of voting rules is performed in a join maneuver. Sanderson and Pitt [SP12] propose an institutionalized consensus approach in platoon applications using self-organizing electronic institutions. Voting mechanisms for leader elections have been used in vehicle coordination in intersection management scenarios as in Ferreira et al. [Fer12]. In [ALV17] vehicular coordination is achieved using consensus for the vehicle leader election.

5.3 Problem and Solution Concepts

Consider a platoon formation composed by a set of vehicles $\mathcal{V} = \{V_1, V_2, ..., V_N\}$, a set of m *alternatives*, for a given context, $C = \{c_1, ..., c_m\}$, and P a list of preferences over C, $\{p_1, ..., p_m\}$. Moreover we assume a payment rule implemented as an auction-based mechanism. We can formalise the platoon formation as a *peer-to-peer* market according the definition in section 3.2:

$$m_{pf} = \langle Part, Art, Reg, Proc \rangle \tag{5.1}$$

where $Part$ are the vehicles and any other infrastructure-agent that might exist to facilitate the platoon formation and control, Art are the payment rules, Reg are the environment regulations, and $Proc$ are allocation protocols (see sub-section 5.4.1). The nature of the market is proposal-based, where a proposal can be triggered either by agents internal or external to the platoon formation.

Each vehicle i has its own behaviour which is defined as an utility function $U_i(c)$ used to evaluate any potential alternative $c \in C$. We consider the perceived utility of the vehicle i for each candidate context $c \in C_m$ is measured using the normalized Gaussian radial basis function based on [San13], detailed in equation 5.2.

$$U_m{}^i(x_m) = e^{-\frac{(x_m - P_m)^2}{T_m}} \tag{5.2}$$

Let M be the set of possible contexts for coordination (e.g. coordinate on what speed to travel at). The utility function (eq. 5.2) outputs a value between 0 and 1 for context $m \in M$ based on the agents preference P_m and its tolerance to deviations T_m for m. The input x_m is the candidate the agent is evaluating in that context

where T_m is a threshold of tolerance for deviation from the context's desired value.

In case we consider more than one contexts the utility function is given as weighted sum of the individual utility functions (eq. 5.3)

$$U = \sum_{j=1}^{m} w_j \cdot {U_j}^i \tag{5.3}$$

where j is the context and U_j is the respective utility function. In order for the platoon to be cohesive and stable the vehicles need to deliberate and reach a consensus over each context active for a given application.

Together with agent's preferences P over some contexts C other agent characteristics of the auction mechanism are:

- **Willingness-to-pay** (wtp) – How much the agent is willing to pay for a resource. Represents the value perceived by the agent of the resource (based on [LVP16]).
- **Endowment** – The amount of monetary units an agent has available for bidding (based on [VO10]).
- **Payment rule** – Either first-price or second-price. Determines how the winning agent should pay for the allocated resource.
- **Auctioneer** – The current agent in charge of the ongoing auction. Bidders submit their bids to the auctioneer which then determines the auction winner.

In this study, auctions empower collective decision-making between autonomous vehicles. We assume the existence of an auctioning module that supports the auctioneer and bidder operations. Such system can be considered as part of the road infrastructure or embedded within each vehicle.

5.4 Collective Decision-Making in Vehicle Coordination

Auctions are market mechanisms focused on reaching agreement over the efficient distribution of resources among autonomous agents. An auction is a protocol that allows a given agent (bidder) to indicate his interest over a given number of resources by offering a bid to an auctioneer (auction manager). Generally speaking, an auction $\epsilon = (\mathcal{B}, \pi, \mu)$ for a set $\mathcal{N} = 1, 2, ..., N$ of bidders consists of:

- the set of bids $\mathcal{B} = (B_1, B_2, ...B_N)$ with a single bid $b_i \in B_i$ for $i \in \mathcal{N}$, and the bid vector $\mathbf{b} = [b_1, b_2, ...b_N]$,
- an allocation protocol: $\pi : \mathcal{B} \rightarrow [0, 1]$, which represents the allocation probability of the resource,
- and a payment rule: $\mu : \mathcal{B} \rightarrow \mathbb{R}^N$ determining the payment each agent has to expect.

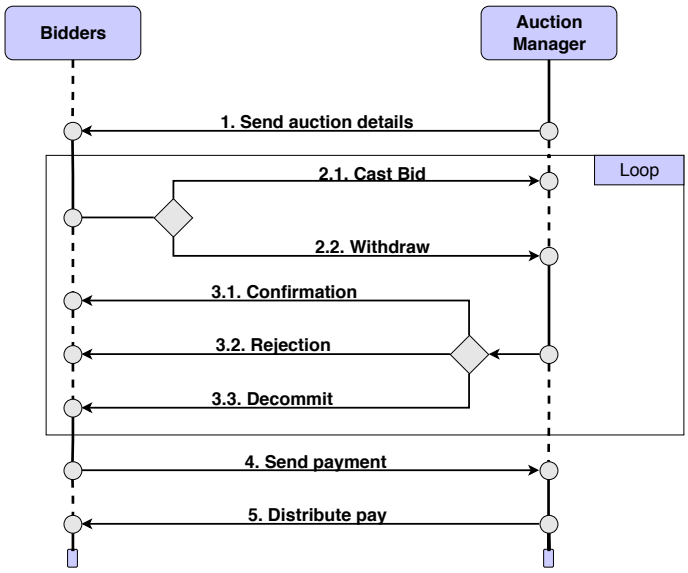


Figure 5.1: General auction protocol

The auctioning module defines bidding rules, payment rules, winner determination algorithms, clearing policy, etc, for the auction. The vehicle bidders send their bids to a vehicle acting as leader of the platoon and auctioneer, which runs a winner determination algorithm. The auction protocol is illustrated in Fig. 5.1 and discussed in the Subsection 5.4.1.

5.4.1 Auction Protocol

The auction is initiated by the auctioneer sending over the auction details to all participants *(step 1)*. The trigger to initiate an auction can vary, e.g. need to alter a property of the platoon or an agent wishing to engage in negotiation (e.g. set the cruising speed of a platoon or when a vehicles wishes to enter a platoon). The contents of the message sent by wireless communications announcing the auction also vary, for example it may or may not contain a starting bid price.

Bidders have the option of sending their bid *(step 2.1)* or withdrawing *(step 2.2)* from the current round of auction. When an agent withdraws from a round it merely states that it will not change its previous bid for that round (i.e. an agent whose bid has surpassed its maximum allotted allowance for that negotiation, will send withdraw messages in the future rounds), which means it can still win if all other bidders fail to surpass its bid. When casting a new bid, the value of the bid must be higher than the previously submitted bid (ascending-bid) to prevent bid manipulation (i.e. to prevent agents from sending very high bids in the first round and then continuously decrease the proposed amount) [VO10]. The auction manager can receive during a predefined time horizon or it can wait until all bids from participating agents are received. After receiving all bids the auction manager runs the winner determination algorithm [VO10] to determine the iteration winner. All bidders are notified of the results via a *Notification of results* message, where if an agent is the winner of a round, receive a Confirmation *(step 3.1)*, a *Rejection (step 3.2)* if they lost the

current iteration, or a *Decommit (step 3.3)* if an agent that was a winner in a previous round is no longer in the winning set.

This process is iterated multiple times, with agents increasing their bids at each round. The break condition can be any type of trigger, e.g. all agents send a withdraw message or four rounds of auctions are completed. Obviously a time limited iterative process could potentially reduce the time taken to reach consensus. Should a tie occur during a bidding round, priority is given to the first agent to send its bid, in a first-come-first-served fashion.

The winner of the auction then sends over the payment *(step 4)* to the auction manager which distributes the payment *(step 5)* over all relevant members if applicable. Note that other more secure payment protocol, such as the one proposed by Isaac et al. [IZC12], could improve the system resilience.

Message transmission occurs via broadcast using dedicated messages for negotiation similar to the protocols developed in [SDC15] and [SBJ+14]. A key difference is that we resort to dedicated broadcast messages, instead of piggybacking acknowledgments in the CAMs. Potential alternatives could also be receiver-based approaches [GHMK16]. The assessment of the most efficient method for reliable message exchange is outside the scope of this work.

5.4.2 Payments and Compensations

We consider the case where we use auctions to coordinate an a-priori formed coalition. In this scenarios, the winning agent will consume its awarded resource and can impact all of the members of the coalition (e.g. the privilege to set the cruising speed of a platoon). In this case, the winning agent will use its allocated resource, potentially affecting all coalition members (e.g., the privilege to set the cruising speed of a platoon). The auction payment is distributed across all platoon elements to maintain adequate agent (vehicle) satisfaction. This is also applied in a similar fashion to when an external agent wins an auction that will influence members of a coalition. In this case the payment is distributed to the affected elements. For example a vehicle that wins an auction to enter a platoon at any position except the last, will give its payment to all elements that must perform any maneuvering needed to allow the vehicle to enter.

Therefore, vehicles can be compensated for their dissatisfaction by receiving some form of payment. The payments are distributed based on an agent's *wtp* (i.e., willingness-to-pay, how much value they assign to a resource) and are considered welfare that can compensate for an agent's dissatisfaction. We define dissatisfaction over a given context m (D_m) as:

$$D_m = 1 - U_m \tag{5.4}$$

The modification in utility due to a payment depends on how much agent i values a given resource, which is represented by their *willingness-to-pay*, *wtp*. As such, the Amortized Utility over a given context m (AU_m) of a vehicle after receiving a monetary compensation δ_i (see equation 5.7) is given as:

$$AU^i{}_m = U^i{}_m + S(\frac{\delta_i}{wtp_i}) \cdot D_m \tag{5.5}$$

where function S is defined as:

$$S(x) = \begin{cases} 1, & \text{if } x \geq 1 \\ 0, & \text{if } x \leq 0 \\ x, & \text{otherwise} \end{cases} \tag{5.6}$$

The payment distribution can be equally split among all elements or distributed according to their evaluation of the resource. In the latter case, agents with a higher *wtp* would receive a larger cut of the payment compared to those with a lower *wtp*, in order to maintain high satisfaction levels. The proportion of the received payment δ_i for agent i is given as:

$$\delta_i = \frac{wtp_i}{\sum_{k=1}^{|R|} wtp_k} \cdot \delta \tag{5.7}$$

where δ is the total payment received from the payer agent (i.e. winner bid), wtp_i is the WTP of the ith agent, R is the set of the agents that lost and wtp_k is the the willingness-to-pay of the kth element in the R set.

This solution guarantees that payment is given to agents that value it the most. However, the disadvantage is that the auction manager will know each vehicles' *wtp*, which can be problematic if the auction manager also participates in the auction (decentralized auctions). An alternative approach is having a trusted third-party distributing the payment to avoid malicious behaviours. Within the scope of this work we assume that no manipulation of the auction exists and that a secure payment method is in place.

5.4.3 Illustrative Scenario

Consider a scenario where the elements of a platoon need to reach consensus along two contexts: (1) cruising speed and (2) route to follow. Each $V_i \in \mathcal{V}$ has a preferred cruising speed $P^i{}_v$ and route $P^i{}_r$, for the same origin and destination. A road network is defined as directed graph $G = (V, A)$, where $V = 1, .., m$ is a set of vertices representing locations (e.g. intersection) and A is the set of arcs connecting the vertices. Additionally, each vehicle i is defined by its willingness-to-pay for a resource, *wtp*, and the endowment *edw*

that reflects the available amount of monetary units.

In this use case, the utility measurement for the cruising speed ($U_v(v)$) (eq. 5.9)receives as input the speed that is being evaluated (v) and the agent's preferred speed P_v. In the context of the route choice however, vehicle i must deliberate over a sequence of vertices forming the preferred route ${P^i}_r$ and an alternative route C_r. We use the Hamming distance to measure the similarity between the two routes, and then we consider the difference $H_{max} - H$ to evaluate the route choice in the route utility function $U_r(H)$. H_{max} denotes the desired maximum similarity between the routes (eq. 5.9). Thus, the utilities for the velocity ($U_v(v)$) and route contexts ($U_r(H)$), and total (U_t) are expressed as:

$$U_v(v) = e^{-\frac{(v-P_v)^2}{T_v}} \tag{5.8}$$

$$U_r(H) = e^{-\frac{(H-H_{max})^2}{T_r}} \tag{5.9}$$

$$U_t = w_v \cdot U_v(v) + w_r \cdot U_r(H) \tag{5.10}$$

where T_v and T_r are the tolerance values that control the rate of speed and route utilities and w_v, w_r are the utilities weights, respectively. Considering the amortized utility in equation 5.5, then the total amortized utility is:

$$AU_t = w_v \cdot AU_v(v) + w_r \cdot AU_r(r) \tag{5.11}$$

The auction-based decision-making process begins when the platoon leader prepares the auction and broadcasts a *NotifyAuction* message according to the protocol (subsection 5.4.1). This type of message is sent to all elements N that are to participate in auction ϵ, alerting them to prepare their bids and providing necessary contextual information, such as the subject m being decided upon. Due to the nature of auctions no "potential candidate" list is sent over and it is assumed that winner agents won't attempt to set invalid properties (e.g. set a speed above legally defined or unsafe limits). After verifying proper receipt of message (i.e. transmitting an ACK message), each vehicle $i \in N$ produces their bid b_i based on its wtp_i and sends it over to the platoon leader, which is acting as the auctioneer. The vehicles' biding process follows an iterative process with gradual increase on bid value limited by their wtp, in an attempt for the agents to pay the least amount possible. The first bid (δ_i) that vehicle i submits is randomly pulled from a gaussian distribution with a mean of $\frac{1}{2}wtp_i$ and a variance of 10. The following bids, ${\delta'}_i$, depend on what set of the auction iteration the agent belongs to. An auction iteration will have a set of agents whose bids were rejected ,R, and a set of agents with wining bids for the current iteration, W, with $W \cap R = \oslash$ and $W \cup R = N$. Due to the design of the auctions, only one element is in W during any iteration. For any given agent i, should $i \in R$ then ${\delta'}_i = \delta_i + \frac{1}{4}wtp_i$ iff ${\delta'}_i \leq wtp_i$, in which case ${\delta'}_i = wtp_i$. Vehicle i will *withdraw* from the current iteration if $i \in W$ or if the bid δ of the last round was equal to wtp_i.

When an agent has its bid ready, it sends it over to the platoon leader in a *Bid* message. The platoon leader adds all the bids to set of bids B which is passed along to the auction module to determine a winner. The auction module will produce sets W and R, that

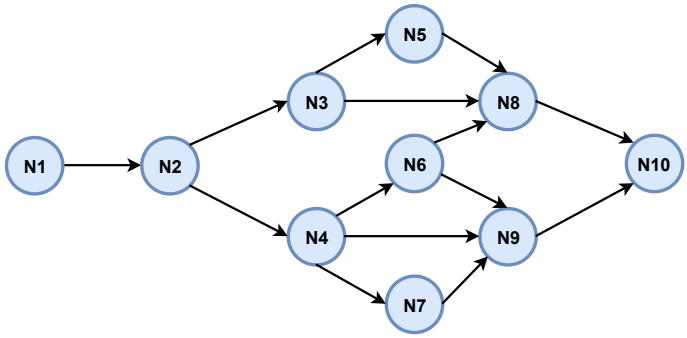


Figure 5.2: Illustrative scenario route network

are broadcast to all elements in N using an *IterationResults* message, containing relevant information about the current auction (e.g. who won and who was rejected). Agents then cast their bids again and this process iterates until either a limit of 4 iterations has been reached or all agents *withdraw* from the current auction iteration. Auction results are sent over with the *AuctionEnd* message, specifying the winner and the amount due according to equation (5.7).

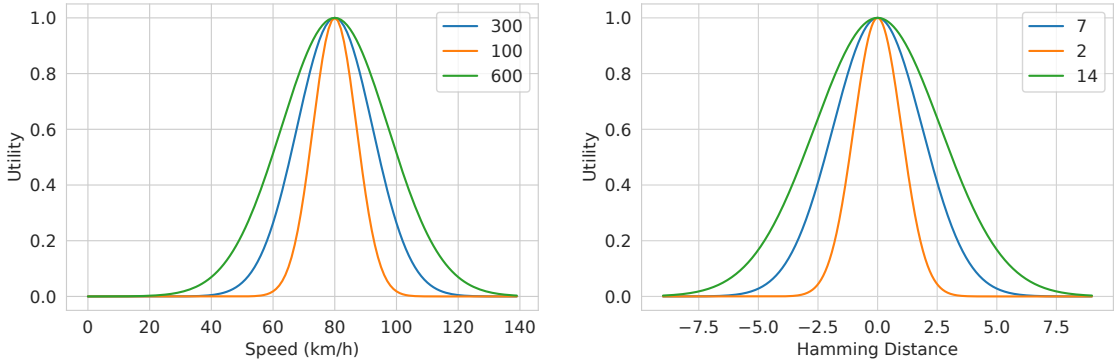
5.5 Experimental Setup

In order to perform simulations with the real-world constraints that are expected of a vehicular network, the decision-making agents should interact within an environment that imposes both constraints to wireless communication and on mobility. We have used the simulation framework discuss in chapter-4 for this purpose.

The implemented auction protocol follows the description presented in Subsection 5.4.1. The auctioning module can either use the first-price sealed-bid clearing rule or the second-price (Vickrey auction) sealed-bid. A first-price auction awards the vehicle with the highest bid. In the second-price auction the resource is awarded to the vehicle with the highest bid, but the price it will pay is of the second highest bid. Both rules are explored and compared in terms of their communication overhead and driver satisfaction.

5.5.1 Simulation Settings

The auction occurs in an already formed platoon with a length that varies between 4 and 8 vehicles. The allowed speeds ranges are [85-120] km/h with 5 km/h increments. The route map used throughout all experiments is depicted in Fig. 5.2. The route is an acyclic unidirectional graph that leads from node N1 to node N10. The platoon is formed and the negotiation takes place in arc N1-N2; all elements have N10 as destination. The scenario consists of a three-lane highway.



(a) Speed utility function per T_v value

(b) Route utility function per T_r value

Figure 5.3: Comparison of tolerance values for speed and route

Regarding the vehicles preferences, the tolerance value for speed (T_v) and route (T_r) are 300 and 7, respectively. In Fig. 5.3 the reader can observe how different values of the context m (i.e. speed (T_v) or route (T_r)) affect the rate at which utility changes as x_m strays further from the agent's P_m. In Fig. 5.3a, an example for the speed utility is presented, with $P_v = 80$ km/h and in Fig. 5.3b the example for route with $H_{max} = 7$. As can be observed higher T_m values decrease the rate of change while lower values increase the rate of change (inversely proportionate). The endowments of each vehicle are generated from a normal distribution of mean 200 and variance 25, retrieved in [VO10], but with the double mean value in order to ensure all agents have at least higher endowment than their *wtp*. The *wtp* is also randomly generated from a normal distribution of mean 50 and variance 20, based on [LVP16], however increased by one order of magnitude. Endowment and *wtp* are measured in monetary units (*mu*), and no specific value is assigned.

Moreover, we assume that travelling alongside the platoon is a traffic flow of approximately 90 vehicles/km, sending beacons of positional data at 100 ms intervals. The two-ray propagation model is used in the simulations [SGD11].

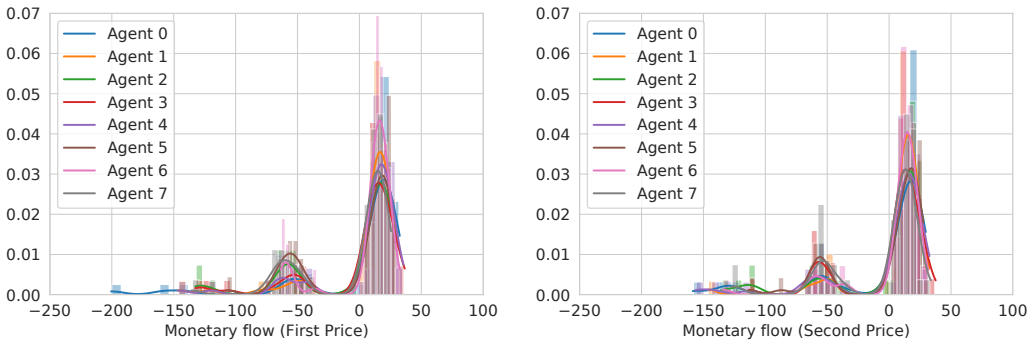
5.5.2 Metrics

To evaluate the goodness of the auction-based coordination in the given scenario we will consider the following metrics:

- **Platoon Utility** The amortized total utility of the platoon at any given moment. The utility of the platoon can grouped either: (a) an *utilitarian*, or (b) an *egalitarian* perspective. The utilitarian social welfare considers that the utility of the platoon is equal to the sum of the utilities u_i of every agent i. The egalitarian social welfare assumes that the utility of the platoon is the one of its vehicles with the smallest utility. Here the *utilitarian* perspective is the sum of all utilities, normalized according to the size of a platoon in order to facilitate comparisons. For both perspectives the goal is to maximize U.

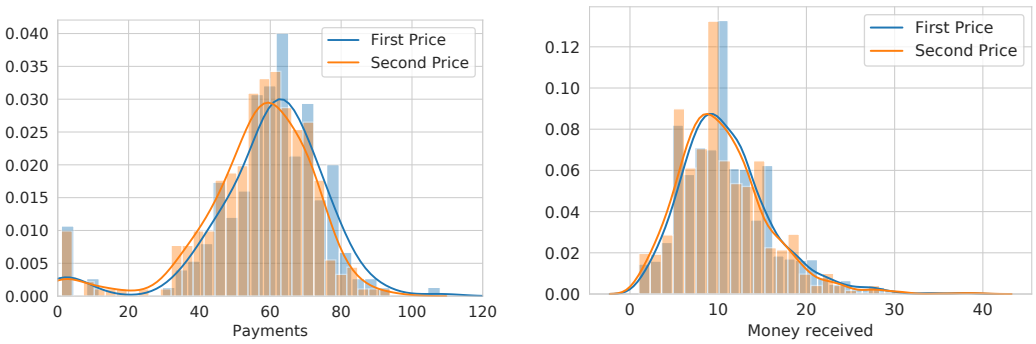
- **Time to consensus (TtC)** The time interval between the start t_s and conclusion t_e of an election or auction including all iterations needed to reach consensus. As the traffic environment is dynamic, the lower the time needed to reach consensus, the better. As such the goal is to minimize TtC. The TtC is measured for each candidate being chosen, with TtC_s measuring the time taken to choose a cruising speed and TtC_r the same for choosing a route. All consensus, in this simulation study are performed sequentially, however they could be performed in parallel and would be bottlenecked by the slowest consensus.

5.5.3 Results and Discussion



(a) First Price **(b)** Second Price

Figure 5.4: Distribution of the monetary flow

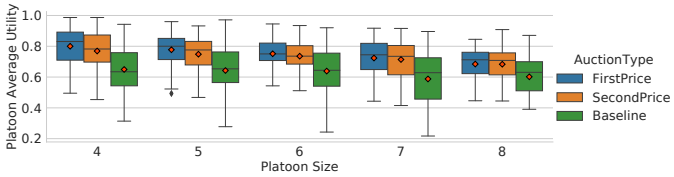


(a) Payment distribution **(b)** Received distribution

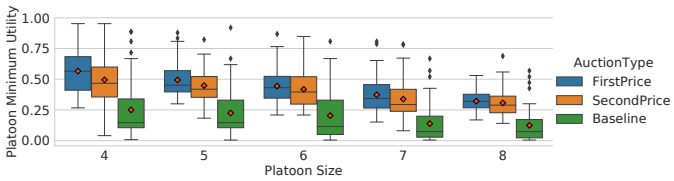
Figure 5.5: Payment and received distributions

Monetary Flows: Figs. 5.5 and 5.4 show the distribution of wealth according to each auction rule. Specifically, Figs. 5.4a and 5.4b show the total monetary flow (payment and receipt) from all auctions the First-Price and Second-Price rules for each individual agent at a platoon size of 8, respectively. The results show that on average agents that win an auction will pay roughly 60 monetary units (Fig. 5.5a), while those who lose tend to be compensated with roughly 10 monetary units (Fig. 5.5b) . The second local maximum of the distribution plot (Fig. 5.4) shows that winning agents tend to have a loss, if they won any one auction, they will not earn back their previous investment if they lose any other auction. As such, consecutive wins will eventually drain the agents allocated budget, preventing them from continuously enforcing their preference over the platoon. This may

prove useful for the overall stability of the platoon, as payments are large and receipts low, it would be wise of the agent to not constantly bid the highest amount. This allows for other agents to have a turn at enforcing their preferences, instead of allowing a very wealthy agent to control the parameters of the platoon. Only a slight difference is observed in the payout of the First-Price or Second-Price rule, which is diluted during distribution between losing agents. With no other apparent differences, the Second-Price rule is potentially the optimal choice for this auctioning scenario, given its properties towards enforcing truthfulness [YS09] within an agents bidding strategy.



(a) Utilitarian



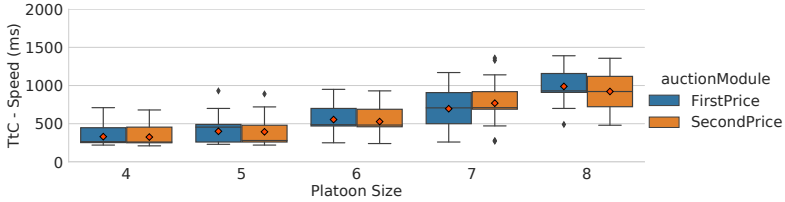
(b) Egalitarian

Figure 5.6: Platoon Welfare in terms of Average and Minimum Utility for Utilitarian and Egalitarian perspectives, respectively.

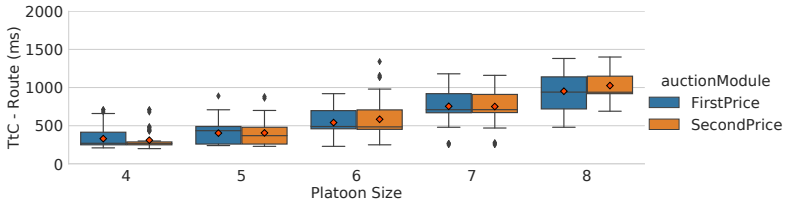
Platoon Utility: The results for driver satisfaction are given in Fig. 5.6a and are compared against a baseline of a "dictatorship" consensus. Both auction rules score a welfare level much higher than the baseline. However, there is no significant difference between the two rules. The first-price rule produces a very slight increase in welfare over the second-price auction, which is to be expected due to the higher paid amounts. As expected, with more vehicles in the platoon, the amount received by non-winning bidders gets diluted, leading to a continuous decrease in welfare. The benefits of the first-price rule (i.e. higher payments leading to higher satisfaction in individual agents) also become less apparent, matching almost exactly the results of the second-price rule at a length of 8. From an utilitarian perspective, it appears that the second-price rule is the optimal choice for collective decision-making, since for a very small loss in satisfaction, the agents can benefit from the advantages of the second-price auctions (i.e. ensure truthfulness).

Similar behaviour is also seen in the egalitarian perspective in Fig. 5.6b, with a noticeable difference between first and second rule at low platoon sizes, but quickly becoming less apparent as sizes increase. Both rules outperform the baseline, while at a small cost to utility the second-price rule can be used for its benefits. The elitist perspective is omitted from the results, as all values are perfect. This is to be expected as the baseline guarantees maximum utility for the leader while the auction rules both give maximum satisfaction towards the winner of the auction.

Time to Consensus: The metrics regarding the impact of an unreliable communication channel are illustrated in Fig. 5.7. The time to consensus metric is defined as the time interval between the start and the end of the iterative process. The time to reach consensus on both speed (Fig. 5.7a) and route (Fig. 5.7b) are similar and both do not exceed the



(a) Speed



(b) Route

Figure 5.7: Time to consensus on each auction

typical time horizon for tactical level decision-making ($\leq$ 2 seconds). The auction rule used appears to not have an effect on the duration of the auctions. However an apparent exponential growth can be seen for increasing platoon sizes. Extrapolation of the obtained values would indicate that the communication latency induced could very quickly make the auction mechanism unfeasible. A potential line of future research is the development of protocols for large-scale auctioning.

5.6 Summary

In this chapter, we explored the use of auctions for tactical level decision-making for platooning coordination. These mechanisms were evaluated under near-realistic constraints (e.g. unreliable communications and realistic vehicle kinematics) resorting to the developed hybrid simulation framework. As a proof of feasibility, two auction clearing rules are compared: the first-price and the second-price sealed-bid auctions. Both rules are tested according to their impact on coalition welfare and communication.

From a communication perspective, a non-negligible delay is present, and should be taken into account when implementing an auctioning mechanism for real-world deployment. At the scale tested (auction groups of 8 members or less), the induced latency is well below the time limits for tactical level decision-making (less than 2 seconds). However an exponential growth of time to consensus as function of size is apparent, which would make real-world deployment at large scales unfeasible. Future research would look into developing an auction protocol that can scale adequately in a vehicular setting.

The results on platoon welfare show very small differences between the first-price and second-price rules. At small platoon sizes the first-price rule grants higher welfare from an utilitarian and egalitarian perspective, however welfare differences between the two quickly become insignificant as the size of the platoon increases. As such the second-price rule is more beneficial, as at a very small cost to welfare, the benefit of enforcing truthfulness can be obtained. Future work will look into combinatorial auction mechanisms.

Distributions of payment show that any given winner agent will have negative revenue unless the bidder loses multiple auctions. As such it would be wise of an agent not to constantly bid in an attempt at winning every auction. The current approach to distribution of payment uses the value an agent attributes to a given resource as a factor.

Chapter 6

Climate Intelligence Support System for Smart and Sustainable Mobility

6.1 Introduction

The triptych cities, mobility and climate change, highlighting recent trends in both developed and developing countries. It is argued that the current situation is unsustainable, and that transport must contribute fully to achieving carbon reduction targets. Following COP26[1], most of the current climate change narrative has focused on mitigation and the lack of substantial emission reduction objectives to keep global warming under 1.5°C. While short-term reductions are crucial to stabilize our future climate, countries must also address the present, escalating physical risk posed by rising climate volatility, which is already built into the system. To address climate hazards, risks and their components must be identified, analyzed, and controlled. Additionally, it has been suggested that risk management should influence climate change adaptation. To address climate risk management and to act upon, a new category of decision support system and data analytics engines has emerged: Climate Intelligence (CI). Climate intelligence, is historical, present, and predictive information about natural and artificial systems that is utilized to power insights for climate mitigation and adaptation. As it has been put "Climate intelligence puts climate at the core of decision-making. Companies, governments and local authorities use it to make climate-aligned decisions"[2]

In this chapter we generalise an architecture for a climate intelligence support system with applications in smart cities. More specifically, we focus on the use of such architecture in applications related to smart mobility and mobility as a service solutions.

The main contributions of this chapter can be summarized as follows:

1. We illustrate the conceptualization of a climate-intelligence decision support framework to design, test, and evaluate actionable policies in domains whose efficiency and sustainability is heavily dependent on how resources are competed by the different actors;

2. We propose several methodological approaches as case studies that implement different elements of the framework, such as:

[1] https://www.un.org/en/climatechange/cop26
[2] https://www.weforum.org/agenda/2021/12/climate-intelligence-climate-change/

- An HLA-based digital twin for assessing an electric bus power-train in realistic traffic settings;
- An econometric analysis of a mixed-fleet buses in public transportation;
- An analysis of eco-driving profiles for electric buses drivers;
- A conceptual framework in representing human behaviour for assessing incentive policies in public transportation.

The remainder of this chapter is organised as follows. Section 6.2 discusses main Climate Intelligence concepts and present an overview of related works. Section 6.3 introduces definitions used throughout this chapter. Furthermore, the conceptual architecture for the support system in electrified mobility is defined. Section 6.4 describes the implementation of the architecture and discuss the achieved results. Finally, Section 6.5 summaries this chapter highlighting its main topics.

6.2 Related Work

New legislative rules and initiatives aimed at altering urban transportation have spawned creative business models to meet the needs of modern communities. A sustainable business model aims for either a more sustainable development with fewer negative effects on the environment, society, and the organization's and stakeholders' long-term prosperity, or adopting solutions that promote sustainability in the value proposition, creation, and capture elements, or in the value network [EVH$^+$17, GVE18].

Business models of modern mobility service providers are increasingly focusing on stakeholder integration, delivery of sustainable services to meet the environmentally aware customer demand, use of advanced digital technologies, and integration of socio-ethical parameters into the product life cycle [LvW21]. [GMRC21] propose a business intelligence system to support the optimized migration towards cleaner vehicle technology for achieving the objectives of zero emissions and green transport as well as to forecast the useful life of these new sustainable vehicles.

Although the fast spread of sharing mobility business models has also greatly strained cities' socioeconomic linkages and physical infrastructures, without necessarily lowering pollution levels. Increased use of shared mobility schemes may not always drive lower CO2 emissions, which might be explained by agents migrating from public transportation to private vehicles. This suggests a strong co-evolution mechanism between macro-level urban system change and micro-level mobility business ecosystem innovation. [MGLB22] suggest that businesses and policies should carefully examine the agents' behavior change to avoid rebound effects through shared mobility concepts. They propose thus an urban mobility decision support framework that integrates the public-private stakeholders into multi-level governance, to define common goals and vision, and then set scenarios and strategies to achieve these goals. [VG21] discusses an evidence-based data-driven decision support framework that consists of a coding method that aims to offer parameters that define a specific policy process to regulate the access of urban vehicles to urban infrastructure with

the objective of dealing with the negative externalities generated by traffic. [RB20, RB22] explore the possibilities offered in terms of coupling between the two concepts, simulation, and business analytics while emphasizing the different architectures implemented to ensure successful cohesion with an indication of works that have covered coupling between analytics and simulation. Despite the very advanced steps that simulation has taken in the world of research, its use in an analytical business environment remains very timid since the work is mainly focused on the descriptive and predictive parts.

[DBN20] analyzes to which degree constraints imposed by vehicle sharing and electrification shape the impact of autonomous vehicles on urban transportation in terms of investments into charging infrastructure of EVs and ensuring demand-supply balance in shared-vehicle systems. To that end, the work explores the combination of real-world data, analytics techniques, and simulation methods to support decision-making through an integrated analysis of these challenges.

[LVVdMD20] proposes a multicriteria approach and a decision support system to support multimodal transportation planning decisions by considering transportation delay, costs, and carbon emissions. [CDE18] proposes using city buses as probe vehicles to provide a thorough view of road congestion and suitable management actions to city authorities, by analyzing the obtained GPS data and producing multiple traffic indices. [YL20] considers an optimization method for the bus rapid transit dispatching problem to determine the vehicle scheduling scheme that minimizes the waiting time for passengers and the energy consumption of vehicles. [CMRV19] propose a framework that supports decision-making regarding the optimization of transport services for people in an effort to minimize renewable energy consumption while ensuring the satisfaction of mobility requirements.

[AWKHS20] introduces a dynamic simulation model to compute a multi-facet key performance index encompassing economic, environmental, and social aspects so that multiple transportation alternatives can be compared and ranked against each other in a multi-criteria decision-making framework. In a similar fashion, [DMEK21] makes use of multi-criteria decision-making approaches to evaluate mode choice alternatives for commuting. [SDWG19] introduce a decision support system that addresses the question of whether it is feasible to build a smart public transportation decision support system that can efficiently use utilize data from shared route segments to produce more accurate predictions. It integrates historical and streaming real-time bus location data from multiple routes for short-term delay prediction as well as long-term delay pattern analytics to provide results to city planners and end-users. [AFR19, AAA$^+$17, BAR15] discuss pattern mining and short-term traffic prediction approaches for better supporting decision-makers.

[KHFD16] discusses, in the context of the "Urban Transport Roadmaps" program, a web-based DSS for urban transport enabling municipal authorities to analyze future mobility scenarios in urban areas, allowing for the comparison of alternative urban structures and the selection of measures for urban transport. The measurable impacts of different policies are based on forecasting macroeconomic trends. The project participants do not take into account any micro-scale traffic consequences of logistics ideas in city areas. The initiatives in the portfolio are restricted to regulatory actions and mobility services. In a more recent assessment, [DNESE19] underlines the necessity of decision support for municipal authorities in the context of urban logistics, as well as the importance of stakeholder participation. Similar conclusion reaches [EF22] where the findings suggest that the role of

freight transportation in Supply Chain management has been under-researched, but several potential challenges have already been identified, thus future research should investigate how to address these gaps. Furthermore, as per definition, a smart city framework is based on innovation and focuses on citizens, therefore research activities should also be aimed at enhancing urban and sub-urban public transportation networks as a whole. As a result, efficient and integrated decision support tools for transportation systems (freight, passenger, or both) are critical for adequately modeling the various planning and management problems, as well as developing efficient solution methods, while dealing with the unavoidable uncertainty of such decisions.

6.3 Conceptual Climate Intelligence Support System for New Mobility Paradigms

In this section we will discuss the conceptual design of a decision support system perspective to provide climate-intelligence actionable recommendations for a transportation system. To ease the description we will focus on a MaaS system and the reason is because this multi-modal, multi-resource, and multi-stakeholder mobility ecosystem is getting increasingly adopted by most large metropolis and medium size cities.

The methodological approach followed in this work bases the development of the Climate Actionable Intelligence Support System platform as an integrated environment that applies model and data driven methodological approaches that allows for the assessment of smart mobility solutions through a multi-metaphor representation of the public transportation domain. The platform is composed of two main components: i) Data & Models, and ii) Behavioural Engine (See Figure6.1).

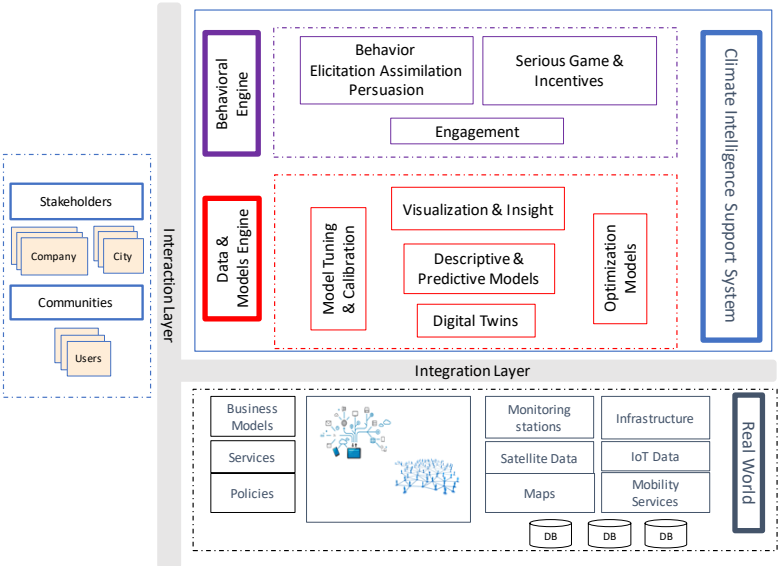


Figure 6.1: A Climate Intelligence decision support system

6.3.1 Actors: Stakeholders and Users

The Climate Intelligence platform herein proposed serves two main groups of users, namely: i) the end-user group or otherwise Business-to-Clients (B2C) users; and ii) the system's stakeholders group, also regarded to as Business-to-Business (B2B) users and the cities. In order to clarify the differences between them, we instantiate the roles in the mobility-as-a-service domain. In this context, we can identify roles such as Regulator/City, Mobility Service Operator, the mobility end-users, Technology Service Providers, and MaaS Operators. Next, we describe each of such roles in more details, also indicating their groups, that is whether they belong into B2C or B2B, or both.

Regulator/City (B2B) coordinates, and moderates mobility services in the jurisdictional entity. It creates the policies and administrative platform that allows MaaS to happen, acting as the catalyst by promoting mobility policies and supporting normative frameworks for open standards adoption, as well as privacy and economic protection for the users. City can be viewed as the principal stakeholder of a MaaS, can achieve the regulator role, or can be seen as a business partner of a MaaS

Mobility Service Provider (B2B) provides mobility services either as direct transportation operator of good and peoples (eg. mass transit, taxi, logistics etc, operator) or as mobility resource manager (e.g bike-sharing provider).

User (B2C and B2B) definition is twofold in our perspective of the climate intelligence support system. From on hand, the user is the person who wishes to use the services for moving something from an origin to a destination (eg. traveller, logistic customer). On the other hand, a user can be the person that operationalizes the mobility services (eg drivers, or bike replenishment operator in a bike-sharing system).

Technology Service Provider (B2B) is the component that provides the technological mobility solutions for the roadside, smart phone apps, wearables, onboard and central systems. In addition, contribute to define open-standards (data and architecture) for IoT generalized presence and work as differentiation enablers for travelers, operators and meta-operators.

MaaS Provider (B2B) acts as an interface between mobility providers end users. Is the component of the MaaS system that optimizes supply and demand, plans journeys, and is responsible for the access and purchase operations for the various mobility modes.

As depicted in Figure 6.2, we can understand how the above defined roles interact and coexist within the proposed Climate Intelligence platform. Its modular and layered architecture is conceived in such a way that all roles are allowed to interact across architecture levels in a seamlessly fashion. A brief description of each layer is provided as follows.

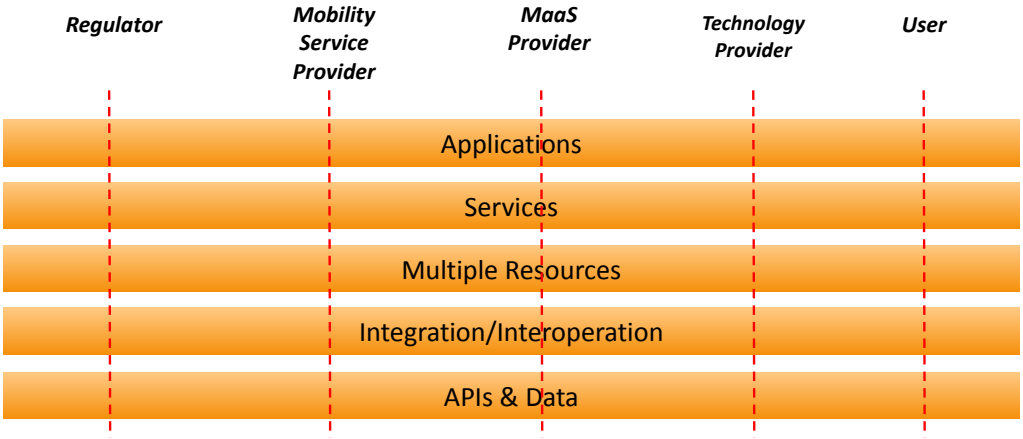


Figure 6.2: An integrated perspective of the roles in the Climate Intelligence support system

- Services: In this layer reside the transport services of people and goods, or the services that facilitate end-users to access the mobility system, such as journey planners, etc;
- Applications: In this layer we intend as applications the mobile apps end-users use to access mobility services, or applications the stakeholders of the system use to monitor its performance. Other type of applications we can consider in this layer are the ones that implement incentive schemes to increase the engagement of a user with the system, or that reward the user for adopting a desirable behaviour (e.g. eco-driving);
- Resources: They can be either physical, such as vehicles, or routes, or human as bus drivers, or other field operators. In both cases we need to optimize some performance aspects related to sustainability;
- Integration/Inter-operation: It is a layer that defines the interaction standards among the different actors/roles
- APIs & Data: It defines the standards and exchange protocols for data collection and processing.

6.3.2 Data and Models Engine

The climate Intelligence Decision Support system builds upon the integration of two complementary analytical perspectives, namely the *data-driven* and the *model-driven* engines. In both engines, their analytical perspectives are made available to users and stakeholders as services, allowing for the automation of the analytical process through concepts such

as (Machine Learning) ML-as-a-Service and Simulation-as-a-Service. Whereas the former profits from much advance in the Machine Learning domain, the latter resorts to the recent and increasing interest in the cross-fertilisation between ML an simulation giving rise to the concept of *Digital Twins*.

As for the data-driven analysis, the platform will resort to the new trends in machine learning automation, namely the concept of AutoML, covering the complete pipeline from the raw dataset to the deployable machine learning model on demand, as required by stakeholders and users. On the other hand, the model-driven strategy make user of simulation tools running under an interoperability runtime environment, allowing for multi-resolution and multi-paradigm simulation models, including the microscopic, mesoscopic, and macroscopic approaches for the mobility system. In this perspective, we explore the intertwine between the data and model engines leveraged on the Digital Twin concept and MASs. In this perspective, expert agents implement the concepts of agent-based data analysis and agent-directed simulation, unleashing a new paradigm combining Machine Learning, agent-based modelling, and agent-directed simulation for decision support.

In order to effectively leverage actionable recommendations by the climate Intelligence Decision Support system, we rely on the requirements for model actionabilty as proposed in [LSMVDS21]. In this work, authors advocate the following requirements:

- Usability: a decision support system should promote seamless and meaningful interaction with the users, requiring an appropriate *user interface*, as well as tools to support the analysis of the *model outputs*;

- Self-Sustainability: decision-support models should present properties such as: *adaptability* to changes in the data distributions (e.g concept drift [GŽB+14]), especially those based on real-time data streams; *robustness* to failures in the data collection infrastructure to cope with possible missing values and other sources of lack of information; *resilience* to keep operating over eventual disruptions in any of its modules; *scalability* to cope with the increase in input data and still keep its performance at acceptable levels;

- Application Context Awareness: decision-support systems should be aware of the scope and limitations to the applicability of the underlying analytical models, which span *operational context*, *regulatory context*, *social & ethic contexts*, and *environmental context*;

- Application Domain Theory: in domain-specific applications of decision support systems, a knowledge base should underlie analytical processes;

- Transferability: From the classical perspective of transfer learning, decision support systems should be able to rely on knowledge obtained from learning tasks applied in a given domain and reuse it on similar tasks in a different domain. In a similar way, We add to this characteristic also the ability to transfer policy strategies, especially with regard to prescriptive models.

6.3.3 Behaviour Engine

We consider the potential integration of serious games along with incentive mechanisms into the conceptual framework of the conceptual Climate Intelligence Support System, whose essence heavily rely on agent-based modeling and simulation. We have already discussed the possibility on integrating serious games and ITS in [RAKG13] to capture and influence human behaviour. Here, we foster the application of serious games as a driver towards social coordination within a more ample domain, tackling sustainability issues in a smart city context considering emerging mobility paradigms.

Capturing behavior characteristics of mobility users so as to grow and breed appropriate artificial societies of agents is a quite laborious task. We performed in [MCKR21] a first effort to conceive a methodology to influence drivers' behavior through incentives and gamification. We have proposed an architecture for a system that addresses the interplay of gamification, the pervasiveness of mobile devices and tradable travel tokens via Blockchain technology. Albeit massive data can be easily acquired through the sensor network technology, cognitive characteristics and decision semantics aren't conveyed as easily. As far as the behavior of users is concerned, we identify three important purposes and abilities of such games:

- *Behavior Assimilation.* This is in line with the primary purpose of gaining new skills, training, and improving certain user abilities. This is the basis for edutainment, and the game can act as a coach that instructs users in the fundamentals of a certain activity and directs learning strategies.

- *Behavior elicitation.* This isn't solely related to monitoring users during the game and generating usage statistics. Elicitation here implies adequate means to capture the semantics of decision-making processes as an attempt at disclosing users' preferences and cognitive abilities. This is of ultimate relevance to the proper understanding of decision-making mechanisms and the implementation of persuasion strategies through incentives.

- *Behavior persuasion.* Contrary to behavior assimilation, persuasion has to do with the ability of the game to evolve behavior and influence certain patterns in the long-term. This mechanism relies on incentive-based policies that aim to induce (not enforce) users to perform certain actions that are more appropriate from the system's point of view [CBH13]. In the case of socio-technical systems, such as mobility systems, this might well serve as an instrument to improve social awareness and coordination.

Assimilating behaviors by the users is a straightforward concept behind serious games; whereas elicitation and persuasion need further clarification, stir up many issues, and pose important realization challenges. In our view, behavior elicitation is a suitable instrument toward a proper representation of the decision-making mechanisms and cognitive abilities of agents forming the artificial society underlying the digital twins of the mobility system. We thus integrate serious games into the conceptual framework of the Climate Intelligence Support System by combining behavior elicitation with the peer-designed agents (e.g in [ES14]), allowing players to feature their peer agents with their own idiosyncrasy.

6.4 Climate Intelligence Engine Implementation for Electrified Mobility

In the following subsections we will showcase a number of studies we have performed in the area of electrified public transportation. We will assume the role of a manager responsible for the public transport services in a city where among the various performance indicators we want to improve is the reduction of the carbon footprint of the city's fleet and the increase in conversion form private car to public transport commuting. Each case study we will show consists in an realization of a component from the climate intelligence framework presented in section 6.3 from a methodological perspective. The subsections 6.4.1 , 6.4.3, and 6.4.4 shows an implementation of the data and model driven components of the *data and models engine*, while the subsection 6.4.5 reflects the incentive component of the *behavioural engine*

6.4.1 Digital Twin for Public Transportation Policy Assessment

The employment of electric buses in metropolitan transportation as an alternative to internal combustion engine buses appears to be a promising sustainable solution. However, an important issue in evaluating the performance and adequateness of such vehicles is being able of representing their operation within a realistic urban environment context. For this case study we consider the implementation of a digital twin of an electric bus performance and the urban environment as the model-driven (digital twin) component of the *data & models engine* depicted in Figure 6.2.

Considering the ATS concept as paradigm for the digital twins framework we should be able to represent all the essential for the evaluation aspects of the real world: the electric bus powertrain, the urban network with its topology and artifacts (i.e. the *supply*), and a group of drivers with their respective behaviours (i.e the *demand*). Here, it is important to define the level of aggregation required for this platform, so as to decide whether to use macroscopic, mesoscopic, microscopic or nanoscopic model resolutions. For the ATS implementation we consider to integrate an electric powertrain bus (EPBS) mathematical model proposed by Perotta et al. [PRRA12] and the SUMO [LBB+18b] traffic simulator. In the following, we overview the two simulation models and discuss their integration following the HLA approach as we have presented in [MKS+13].

According to HLA philosophy, each federate application is an independent application. In this sense, each federate is carefully designed and developed. Figure 6.3 illustrates the main federate components and interactions for the HLA-based digital twins implementation. For the development of the federate applications, two aspects had to be taken into account: one is the communication module with the simulation models, the other is the federate ambassador module for communications with the RTI. The federate ambassador is the module through which all the communication with the RTI is performed.

There are two different groups of methods that are related to the type of data exchange. The first group is directed to the interaction classes and the other, to the object classes. But before exchanging data between federates, the Federation Object Model needed to be

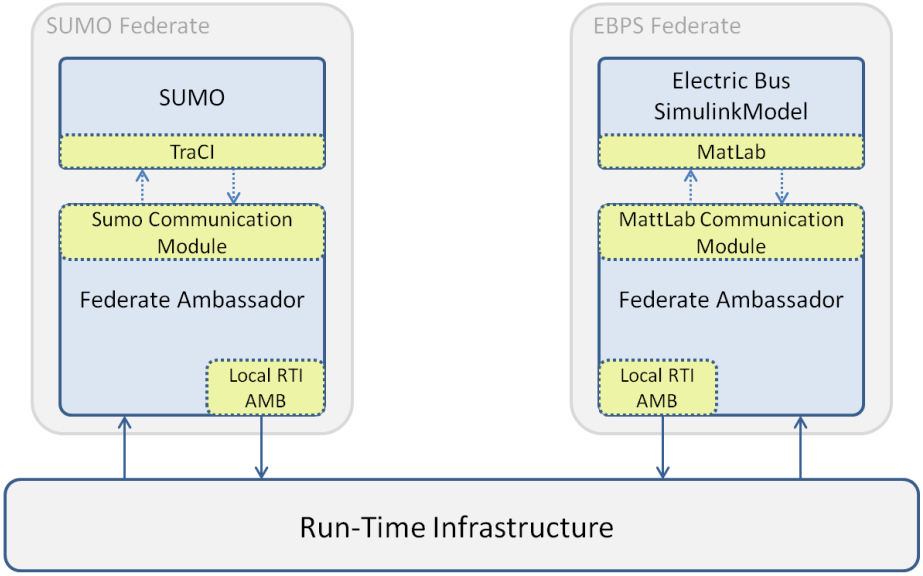


Figure 6.3: HLA-based ATS implementation for Electric buses

specified and the communication module with the simulators needed to be created.

Federation Object Model (FOM) Specification To achieve a coherent and persistent integration among different models HLA standards define the FOM entity where a description of the data exchange in the federation (i.e. the objects and interactions that will be exchanged) is described. This can be seen as the language of the federation. Each federation defines its own FOM, since a federation is defined for a given purpose each time. During the creation of the FOM three of the most important issues to be considered are the Object classes, the Interaction classes, and the Data types. These entities have to be defined well in order to describe the information exchanged between the federates of a federation. In the Table 6.1 is represented the table of the object classes for the federation FOM of the proposed ATS platform.

Specification of Federates There are two different groups of methods that are related to the type of data exchange. The first group is directed to the interaction classes and the other, to the object classes. The interaction classes follow the *publish-subscribe* paradigm to engage the communication between SUMO and EBPS fedearates. The object classes encapsulates the attributes each federate needs to access.

Table 6.2 presents the *InteractionClasses*, *ObjectClass* and *ObjectClassAttributes* Published and Subscribed by each federate.

Table 6.1: Bus Object Class Representation

Attribute	Type	Publish Suscribe
Name	HLAunicodeString	PS
Velocity	VelocityFloat64	PS
Acceleration	AccelerationFloat64	PS
Power	PowerFloat64	PS
Torque	TorqueFloat64	PS
Efficiency	EfficiencyFloat64	PS
TotalCycleEnergy	TotalCycleEnergyFloat64	PS
BrakingKinectEnergy	BrakingKinectEnergyFloat64	PS
BrakingResistanceEnergy	BrakingResistanceEnergyFloat64	PS
SuperCapacitorsChargingEnergy	SupercapacitorsChargingEnergyFloat64	PS
SuperCapacitorsDischargingEnergy	SupercapacitorsDischargingEnergyFloat64	PS
BatteriesChargingEnergy	BatteriesChargingEnergyFloat64	PS

Table 6.2: Publish (P) and subscribe (S) entities by SUMO and EBPS federates

Class Type	Identifier	SUMO	EPBS
InteractionClass	Start	P	S
ObjectClass	Bus	P	S
ObjectClassAttribute	Velocity	P	S
ObjectClassAttribute	Acceleration	S	P
ObjectClassAttribute	Power	S	P
ObjectClassAttribute	Torque	S	P
ObjectClassAttribute	TotalCycleEnergy	S	P
ObjectClassAttribute	BrakingKinectEnergy	S	P
ObjectClassAttribute	BrakingResistanceEnergy	S	P
ObjectClassAttribute	SuperCapacitorsChargingEnergy	S	P
ObjectClassAttribute	SuperCapacitorsDischargingEnergy	S	P
ObjectClassAttribute	BatteriesChargingEnergy	S	P

Now that the federates informed the RTI of what they *Publish* and *Subscribe*, they have to implement the necessary methods for exchanging data during federation execution. These methods are the following:

- registerObjectInstance
- discoverObjectInstance
- updateAttributeValues
- attributeOwnershipAcquisition

The *registerObjectInstance* service registers a new object instance of the specified type. When the object is registered by one federate, the RTI will make sure that it is discovered by other federates that subscribe to the specified class using the *discoverObjectInstance* method. The *updateAttributeValues* service sends an attribute update for a particular object instance. Finally, the *attributeOwnershipAcquisition* is used by the EBPS federate to request ownership for some attributes. Since it was the SUMO federate to register the class Bus, by default all the attributes were owned by it and the EBPS could not update any. Calling the *attributeOwnershipAcquisition* service to RTI, it can request the attributes that it want to update and gain their ownership. With all methods implemented, their execution sequence will be performed as illustrated in Figure 6.4.

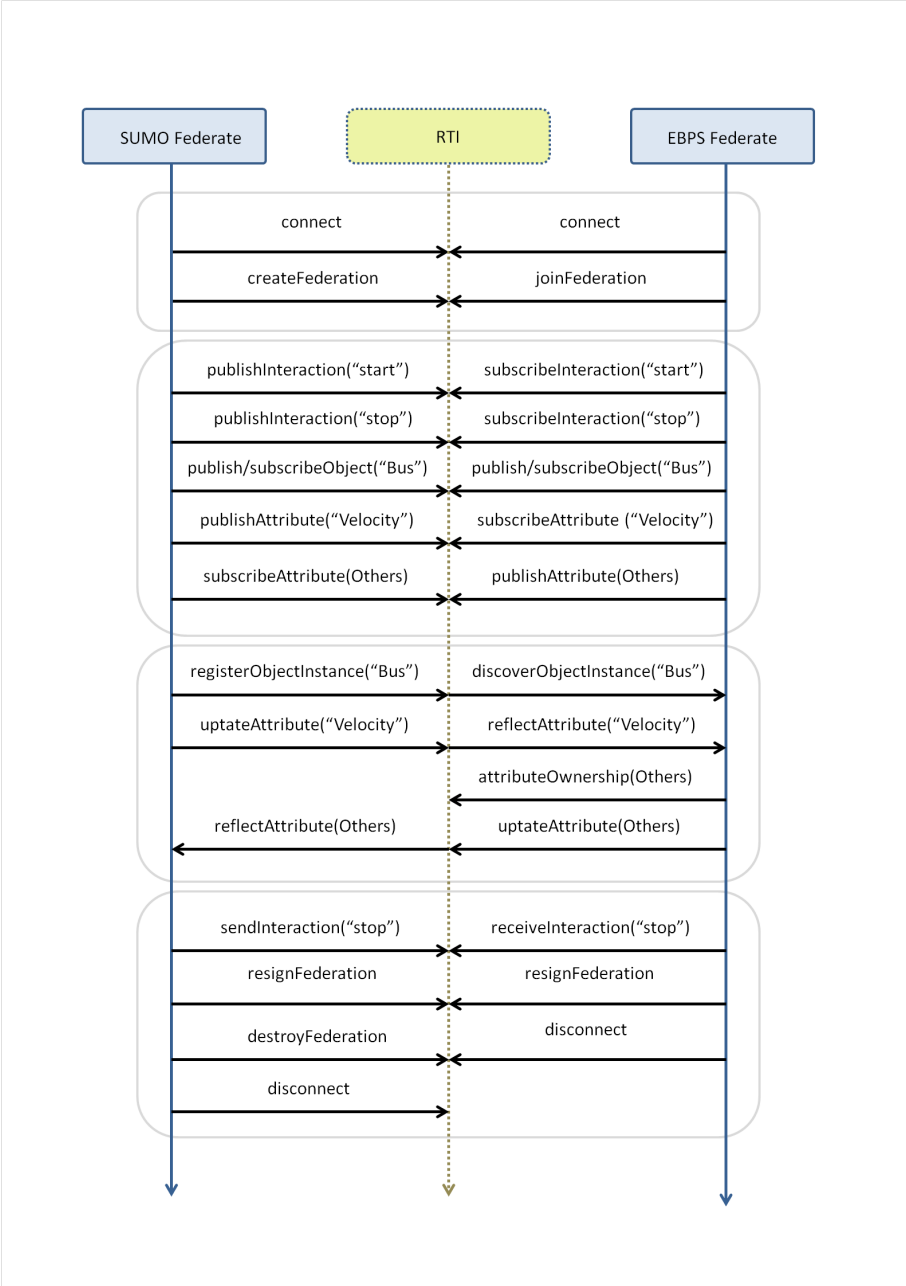


Figure 6.4: Federation execution flow diagram

Short Summary The case study focuses on the implementation of an HLA-based networked framework for electric bus powertrain simulation in urban mobility scenarios, which employs two types of simulation models: the SUMO microscopic traffic simulator and the MatLab/Simulink environment. The approach provides a flexible strategy for coupling two simulators, one from transportation and one from automotive. The goal is to provide a useful tool for traffic managers and practitioners in their efforts to either analyze how network topology affects the operation of electric buses and plan accordingly [PMR+14], or (and other types of electric vehicles) or how traffic flow and congestion affect driving styles and thus the electric bus operation [PMR+13].

6.4.2 Acquiring and Processing Bus Data

For the case studies presented in this chapter we resort to data collected during May 2016 in the mid-sized European city of Porto, Portugal. Specifically, the operational bus data was acquired during a typical week spanning between May 9 and 16, 2016. Porto's metropolitan area has approximately 1.73 million inhabitants living within a territory of about 2000 km^2.

The dataset was provided by the main (public) bus operator [3] of the city of Porto, Portugal. STCP had a fleet exceeding 400 buses most of which were natural gas buses and a decreasing number of diesel buses due to environmental reasons; the company had no electric buses at the time the data was collected, but currently operates 15 of such vehicles. This operator was responsible for 67 urban and suburban bus services (lines), comprising a total travel distance of nearly 490 km. The shortest and longest bus lines have a travel distance of 5 km and 22 km, respectively. The number of bus stops per line varies between 17 and 61. The eleven night lines (operating between 12.00 am and 6.00 am) are not considered in this study due to the different travel characteristics and driver performance. Due to privacy reasons no demographic information on the drivers is available.

All vehicles were equipped with a proprietary telematics system for fleet management and operation, including a GPS device for collecting real-time positioning and status information of every bus. Positioning information was not acquired in regular interval, but most readings were captured approximately every 20-second intervals on average. The collected raw information is given in Table 6.3, which is further processed for improving the data quality. The data cleaning comprised removing or correcting abnormal values of the raw dataset

[3] Sociedade de Transportes Colectivos do Porto (STCP): www.stcp.pt

Table 6.3: Collected raw data fields

Type	Metric	Definition
Vehicle	vehicle id	Identifier of vehicle
Driver	driver id	Anonymously identifies a driver
Service	service number	Identifier of the service
	start timestamp	Service starting time
	shift number	Number of the shift of the working day
Trip	trip number	Identifier of the trip sequence within the service
	start timestamp	Trip starting time
	line number	
	line direction	
Dynamics	timestamp	
	vehicle position	(lat, lon) coordinates
	travel distance	within the service period
	speed	instantaneous speed at time of capture
Bus Stop	next bus stop	identifier of upcoming bus stop
	order position	order position of next bus stop

Dataset characterization. The original bus mobility dataset consisted of roughly 2.8 million data points, totaling approximately 334390 kilometers traveled at an average speed of 18 km/h. Trips with less than 1Km travelled distance and drivers with less than 5 trips were dropped. The processed dataset comprises 757 anonymized bus drivers which have performed approximately 27 thousand trips. The average service and trip duration is 3 h and 45 min, respectively. The average service and trip travel distance is 53.3 km and 12.6 km, respectively. Through proper data aggregation, we select the following attributes to represent driving and trip-based profiles.

For the driving profile information, we aggregated the observed kinematic and energy related variables over the trips performed by a given driver:

- Average speed over all trips;
- Average acceleration over all trips;
- Total number of aggressive acceleration events (acceleration > 5 Km/hs);
- Average breaking over all trips;
- Total number of aggressive breaking events(breaking < -7 Km/hs
- Total number excess speed events (speed > 50 Km/h);
- Average energy consumption per Km;
- Average tailpipe emissions per Km.

For the trip-based dataset, we considered the average values of each attribute observed on a single trip:

- Average speed;
- Average acceleration;
- Number of aggressive acceleration events (acceleration > $5Km/h$);
- Average breaking;
- Number of aggressive breaking events (breaking < $-7Km/h$, as absolute value);
- Number of excess speed events (speed > $50Km/h$);
- Energy consumption per Km;
- Tailpipe emissions per Km;
- Total length of each trip;

- Number of positive and negative elevation variations;
- Average positive and negative elevation variations.

Simulating energy consumption To estimate the energy consumption and tailpipe emission for each trip we used the implementation of the digital twin we discussed in section 6.4.1 to simulate both the electric and conventional buses. The simulation outputs included the total energy consumption, in kWh, for the analyzed trip, along with the percentage of battery drained. For Diesel vehicles, consumption and emission data was calculated using SUMO's *emissions driving cycle* tool[4]. The evolutionary solver was then run individually for each day within operation period from 09/05/2016 to 16/05/2016 (Monday to Monday). The model inputs are the instantaneous acceleration and speed profiles and the electric vehicle characteristics (e.g. frontal area mass). The bus data used hereafter is model EL2500, manufactured by the Portuguese company CaetanoBus [5]. This electric bus uses a brush-less permanent magnetic electric motor, with 650 N.m peak torque and 150 kW peak power. Motor efficiency data was extracted from the supplier's plot of motor efficiency versus motor speed and a mathematical equation was deducted from it. Table 6.4 shows the necessary parameters used to perform the simulations:

Table 6.4: Electric bus specification

Parameter	Value
Tire Radius	0.5 $[m]$
Road Surface Coefficient	1.2
Vehicle Frontal Area	10 $[m]$
Gravitational Acceleration	9.8 $[m/s^2]$
Aerodynamic Drag Coefficient	1.17
Air Density	1.2 $[kg/m^3]$
Vehicle Mass	17,048 $[kg]$
Controller Efficiency	92%
Gear Ratio	First Gear: 1:3 Second Gear: 1:1 Differential: 8.83

The output of the model are the energy consumption (kWh/km), the instantaneous power (kW) and the State-of-Charge (SoC) of the battery (%). For the purpose of the following studies described in the next subsections we make the assumption that the battery is fully charged (SoC = 100%) at the beginning of each trip.

6.4.3 Mixed-Fleet Optimization model

In the EU, urban mobility already accounts for 40% of all CO2 emissions of road transport and up to 70% of other pollutants from transport . Congestion and pollution are becoming increasingly visible as cities grow in size, particularly in bigger cities. As a result, one of the major obstacles in the shift to more sustainable energy production is the transportation

[4] `http://www.sumo.dlr.de/wiki/Tools/Emissions`
[5] http://www.caetanobus.pt

sector. Implementing robust public transportation infrastructure, such as bus service, is a viable approach to minimize the amount of private passenger vehicles on the roads. Combining this concept with that of transportation electrification for emission reduction, electric buses in public transportation are an intriguing answer to both urban disorder and growing pollution levels caused by transportation.

It is important, however, to recognize that electric vehicles are not a "one-size-fits-all" solution, as Ribberink and Entchev [RE13] point out. First, electric vehicles still have limitations in comparison to their conventional counterparts. Second, it is probably not feasible for a transportation entity to completely replace existing conventional vehicle fleets by electric ones. Third, as Ribberink and Entchev studied, a sudden proliferation of electric vehicles will impose a significant load on the existing power grid, having economical and environmental consequences.

Fleet management include managing fleet activities at various strategical, tactical, and operational levels, for various modes of transportation and a wide range of duties such as vehicle routing, fleet composition, vehicle scheduling, and fleet monitoring. The focus of this case study is to propose methods to improve the performance of these mixed bus fleets while reducing pollutant emissions and energy consumption without jeopardizing service quality. As part of a Climate Intelligence support system, we propose an optimization approach, as part of the *data & models engine* (*otimization model*) block, to find the best possible allocations of electric buses to sets of bus trips, balanced with conventional buses in the same fleet. Results of this research were first reported in [SKdS+16]

6.4.3.1 Objectives

Our objective is to address the aforementioned concerns considering a robust implementation of *mixed bus fleets*, composed of electric vehicles and their conventional counterparts. This implementation brings about several questions one should answer:

- How can we *estimate the performance* of electric vehicles when employed in mixed bus fleets?
- How can we obtain an *ideal balance* between conventional and electric vehicles?
  - ***How many*** vehicles of each type should the fleet be composed of?
  - ***Where*** should we allocate each type of vehicle?
- How can we *optimize* these fleets, considering:
  - Energy consumption;
  - Environmental impact;
  - Overall economic impact;
  - Service quality.

We propose to answer these questions by analyzing how to find the optimal balance between the number of electric vehicles and conventional vehicles in a bus fleet, considering the number of vehicles of each type, and where to allocate them. As previously mentioned, we want not only to find the best cost for the overall fleet, but also reduce the emission of pollutants as much as possible. By studying the solutions in a *Pareto frontier*, we can simultaneously consider the different trade-offs between the objectives.

6.4.3.2 Problem Formalization

The theoretical formalization of the problem considered is as follows.

First we define a set, $V = \{v_1, ..., v_n\}, v_i \in \{0, 1, 2\}$, of n *integer* decision variables, corresponding to the n different vehicles in use during the period of operations being studied. Each variable can have a value of 0, 1 or 2, representing an *electric bus*, a *CNG bus* or a *Diesel bus*, respectively.

There is also a set $T = \{t_1, ..., t_m\}$ of m individual trips to be performed by vehicles. For each trip $t_j (i = 1, ..., m)$ there must be one and only one vehicle allocated to perform it. However, a single vehicle, v_i can perform any number of different trips, without repetition. As such, to each individual vehicle v_i, there is a unique set of bus trips, $S_i \subseteq T, i = 1, ..., n, S_a \cap S_b = \{\}, \forall a \neq b$, associated, described by the operational data being studied.

To each vehicle v_i there is an associated initial cost of purchase, c_i, and a discount to this cost, $p_i \in [0, 1]$. At the moment, discounts correspond to each of the three different vehicle typologies taken into account. As such, for example, if the discount ratio for electric vehicles is 0.3, all the electric vehicles will benefit from that discount in the cost function. Similarly, vehicle purchase prices are fixed values different according to the vehicle type. Equation 6.1 summarizes these rules. The actual vehicle cost and discount values vary according to the scenario being studied. Subsection 6.4.3.4 describes the values for the STCP scenario considered.

$$c_i = \begin{cases} c_{electric}, & \text{if } v_i = 0 \\ c_{cng}, & \text{if } v_i = 1 \\ c_{diesel}, & \text{if } v_i = 2 \end{cases}, p_i = \begin{cases} p_{electric}, & \text{if } v_i = 0 \\ p_{cng}, & \text{if } v_i = 1 \\ p_{diesel}, & \text{if } v_i = 2 \end{cases} \tag{6.1}$$

To each vehicle and trip pair, there is an associated fuel (or energy) cost, f_{ij} and a pollutant emission value, e_{ij}. Similarly to the vehicle costs, fuel costs can also have an associated discount, q_i, that depends on the type of fuel being considered. Equations 6.2 and 6.3 describe these conditions. In addition, for vehicles allocated to the electric vehicle type, b_{ij} represents the total battery spent by the vehicle i in trip j, in percentage. Again, specific values for fuel costs and emissions depend on the scenario at hands and the values for the STCP scenario considered can be found in Subsection 6.4.3.4.

$$f_{ij} = \begin{cases} f_{electric_j}, & \text{if } v_i = 0 \\ f_{cng_j}, & \text{if } v_i = 1 \\ f_{diesel_j}, & \text{if } v_i = 2 \end{cases}, q_i = \begin{cases} q_{electric}, & \text{if } v_i = 0 \\ q_{cng}, & \text{if } v_i = 1 \\ q_{diesel}, & \text{if } v_i = 2 \end{cases} \tag{6.2}$$

$$e_{ij} = \begin{cases} e_{electric_j}, & \text{if } v_i = 0 \\ e_{cng_j}, & \text{if } v_i = 1 \\ e_{diesel_j}, & \text{if } v_i = 2 \end{cases} \tag{6.3}$$

Given the previously stated equations, we can now define the problem as a *multi-objective, constrained, integer optimization problem.* We need to find an allocation of vehicle types to the set of vehicles, V, in order to:

Minimize

$$E(V) = \sum_{i=1}^{n} \sum_{j=1}^{|S_i|} e_{ij} \tag{6.4}$$

$$C(V) = \sum_{i=1}^{n} \left(c_i \left(1 - p_i\right) + \sum_{j=1}^{|S_i|} f_{ij} \left(1 - q_i\right) \right) \tag{6.5}$$

Subject to

$$\sum_{j=1}^{|S_i|} b_{ij} \leq 100, \{i | v_i = 0\} \tag{6.6}$$

$$\frac{|V_{cng}|}{|V|} \leq r_{cng}, V_{cng} = \{v | v = 1\} \tag{6.7}$$

$$\frac{|V_{diesel}|}{|V|} \leq r_{diesel}, V_{diesel} = \{v | v = 2\} \tag{6.8}$$

Equation (6.4) defines the first objective to be minimized, the total pollutant emissions during the period of operations for the fleet of vehicles configured, $E(V)$. To remind, these pollutant emissions are composed of CO_2, CO and NOx emissions, converted to carbon dioxide equivalent units. Equation (6.5) defines the second objective, the total cost for the operations period and configured vehicle fleet, $C(V)$, including initial cost to acquire each different vehicle and possible discounts in purchase and fuel prices.

To assure the validity of the problem we define three constraints. Constraint (6.6) assures no electric vehicle performs a set of trips that exceeds its total battery autonomy. Constraints (6.7) and (6.8) allow the specification of a maximum ratio of CNG and Diesel vehicles, respectively, to be used in the fleet.

6.4.3.3 Evolutionary Algorithm Solution

Multi-objective optimization problems are frequently solved using evolutionary algorithms, in the literature. With each extra objective to optimize, the computational complexity grows and the number of possible solutions grows as well; Usually, a single, optimal solution ceases to exist and we need to consider a *Pareto frontier* of solutions [CLV06]. This frontier represents the different solutions for which it is impossible to improve any objective without making at least one of the others worse.

Diesel buses, while cheaper, are often more pollutant than their electric and compressed natural gas counterparts. Thus, there are necessary tradeoffs between pollutant emissions and cost reduction. The number of vehicles in the bus fleet represents the number of decision variables in our optimization problem. Since this number varies with the scenario being studied, growing large if more than a single day is considered, evolutionary algorithms seem like a good first approach. To solve the optimization problem we opted to use the NSGA-III algorithm [DJ14], a variation of the *Nondominated Sorting Genetic Algorithm* (NSGA) [SD94], implemented using the *MOEA Framework* [6].

6.4.3.4 Experimental Setup

The first set of experiments included the vehicle purchase costs in the solver's cost function. The solver was run once for each day of the entire period of operations while considering only CNG and Diesel buses in the fleet, with a maximum of a 50% ratio of CNG buses. These runs had the objective of gathering data in a fleet scenario consistent with STCP's current one, with no electric buses, in order to serve as a comparison baseline. Then, the solver has executed again for the whole period of operations, but this time considering electric vehicles in the fleet. The second set of experiments consisted in the same procedure as the first one, but now without considering vehicle purchase costs, in order to evaluate allocation outputs based on the cost impact solely related to fuel and energy costs. After analyzing and comparing these two sets of experiments, a brief sensitivity analysis was performed on the variation of electric vehicle purchase cost and extra battery autonomy.

For reference, Table 6.5 summarizes the input values used in the experiments, along with their respective sources. CNG and Diesel vehicles' purchase costs were based on average estimations [SKdS+16].

6.4.3.5 Results

1. **Solver results considering initial vehicle purchase costs**

[6] `http://www.moeaframework.org/`

Table 6.5: Reference of input values used and respective sources.

Parameter	Value	Description
Electric Vehicle Cost	500 000 €	Initial purchase cost of a CaetanoBus 2500 EL electric bus [SKdS+16].
CNG Vehicle Cost	180 000 €	Estimated initial purchase cost of a CNG bus [SKdS+16].
Diesel Vehicle Cost	150 000 €	Estimated initial purchase cost of a Diesel bus [SKdS+16].
Electric Bus Purchase Discount	0% - 50%	Discount on the initial purchase cost of an electric bus.
CNG Bus Purchase Discount	0%	Discount on the initial purchase cost of a CNG bus. (Not considered in this study.)
Diesel Bus Purchase Discount	0%	Discount on the initial purchase cost of a Diesel bus. (Not considered in this study.)
Electricity Cost	0.1402 €/ kWh	Price of electricity per kWh. Retrieved from electricity cost for industry, in Portugal [SKdS+16].
CNG Fuel Cost	0.0009 €/ g	Price of CNG fuel, per gram [SKdS+16].
Diesel Fuel Cost	0.0011 €/ ml	Price of Diesel fuel, per milliliter [SKdS+16].
Electricity Discount	0% - 50%	Discount on electricity costs.
CNG Discount	0%	Discount on CNG fuel costs. (Not considered in this study.)
Diesel Discount	0%	Discount on Diesel fuel costs. (Not considered in this study.)
Electric Bus Energy Consumption	Variable, in kWh	Energy consumption for a particular trip, as simulated with the Simulink model.
CNG Bus Fuel Consumption	510 g / km	CNG fuel consumption for a particular trip [HJF+13].
Diesel Bus Fuel Consumption	Variable, in ml	Diesel fuel consumption for a particular trip, based on HBEFA [KKH+99, INF16].
NOx GWP	68	NOx global warming potential over 100 years [LA90].
CO GWP	2	CO global warming potential over 100 years[LA90].
Diesel CO_2 Emissions	Variable, in mg	HBEFA CO_2 emissions for a Diesel bus, for a particular trip [KKH+99, INF16].
Diesel NOx Emissions	Variable, in mg	HBEFA NOx emissions for a Diesel bus, for a particular trip [KKH+99, INF16].
Diesel CO Emissions	Variable, in mg	HBEFA CO emissions for a Diesel bus, for a particular trip [KKH+99, INF16].
CNG CO_2 Emissions	72% of Diesel values	CNG bus CO_2 emissions relative to a Diesel bus, for a particular trip [POR01].
CNG NOx Emissions	20% of Diesel values	CNG bus NOx emissions relative to a Diesel bus, for a particular trip [Roc01].
CNG CO Emissions	50% of Diesel values	CNG bus CO emissions relative to a Diesel bus, for a particular trip [Roc01].
EV Emissions (CO_2 + NOx + CO)	0	Electric bus tailpipe emissions (none).
Extra Battery Percentage	0% - 100%	Percentage of extra battery allowed when studying electric bus autonomy.

As mentioned before, the first set of experiments made were with vehicle purchase costs considered in the cost function, evaluated over the operations period of 09/05/2016 to 16/05/2016. Each day generated an approximate *Pareto frontier* of around 100 solutions. From these, three solutions for each day were selected as representative of the frontier. (i) The *emissions trade-off* solution type attempts to minimize the pollutant emissions, at the expense of increased total costs. (ii) The *total cost trade-off* minimizes total overall cost, at the consequence of increased pollutant emissions. (iii) The median emissions and total cost type of solution take on a "best of both worlds" approach, representing a middle-ground between emissions reduction and total cost minimization. Of the three types of trade-offs, only the one focusing on optimizing emissions allocated electric buses to the fleet, in the solution respective to 12/05/2016. In addition, the corresponding emissions value and total costs were higher for that day, in comparison with the baseline solution, showing that specific fleet configuration to actually be worse than the corresponding solution without electric vehicles. Due to the absence of electric vehicles in the fleet in the rest of the solutions shown, those specific fleet allocations will not be discussed any further. Subsection 6.4.3.6 may help understanding the reasons for these results.

2. **Results considering fuel costs and pollutant emissions only**

A suite of experiments similar to the one in the previous paragraph was performed without considering vehicle purchase costs in the solver. The resulting solutions were evaluated in a similar manner as well, by selecting the ones according to the same emissions and total cost trade-off, as well as the median solutions in the *Pareto* frontier. It was possible to see that, in comparison with the previous analysis, the found solutions now consider electric vehicles in the fleet every day. Weekend operation days were not considered in the comparisons with the baseline values, due to the significant difference in the number of trips and fleet composition. For the sake of brevity, only the median valued solution analysis is described in detail in this document, since it represents the most balanced approach when considering both objectives.

The analysis of solutions on the "middle-ground" of pollutant emissions to fuel costs shows a reduction in emissions for every single day of operations under study, along with a corresponding reduction in fuel costs. Summed up, these differences account for a total reduction of 9519 kg CO_2e in pollutant emissions and a reduction in costs of 1350 €, as shown in Table 6.6. As expected, while not witnessing emissions or cost reductions as large as in the other trade-off analyses, we see steady improvements when comparing with all the baselines for the other types of solutions. These values are shown in Table 6.7.

Table 6.6: Reduction from baseline values for middle-ground (median) solutions (purchase costs not considered).

Operations day	**Emissions** (kg CO_2e)	**Total cost** (€)
09/05/2016	2072.83	329.54
10/05/2016	1660.04	203.35
11/05/2016	1244.43	269.53
12/05/2016	1918.21	208.49
13/05/2016	1285.06	191.88
16/05/2016	1338.40	148.03
Total	9518.98	1350.83

For the emission reduction favoring trade-off, emission reductions are of approximately 8161 kg CO_2e and fuel cost savings amount to €1765, comparing to the respective baseline. Solutions favoring total cost reduction show reductions of 12131 kg CO_2e in emissions and €1010 in total costs. However, the emission reduction trade-off is more expensive when compared to the total cost favoring baseline, while less pollutant; the total cost trade-off, on the other hand, is more pollutant than the emission reduction favoring baseline, but less expensive.

Table 6.7: Emission and cost reduction for median valued solution type, in comparison with the baseline values.

	Emissions (kg CO_2e)	**Total cost** (€)
Versus emission favouring baseline	4822.37	2851.69
Versus cost favouring baseline	17277.70	459.92
Versus median valued baseline	9518.98	1350.83

3. **Studying fleet costs**

   We must consider the importance of the added cost to buy an electric bus when making fleet management decisions. As such, the purchase costs were used to evaluate the solutions devised by the solver after-the-fact. Using the same set of solutions considered so far in this analysis, a study on the total cost of the bus fleets was made. The average baseline fleet was considered to be composed of 191 CNG buses and 191 Diesel buses. For the average fleet with electric vehicles, the composition considered was 24 electric buses, 191 CNG buses, and 167 Diesel counterparts. The total length of these fleets is 382 vehicles. Considering the vehicle purchase costs in Table 6.5, we have a total value of €63 030 000 for the baseline fleet. As for the mixed EV fleet, we get a total cost of €71 430 000, hence a 13%, or €8 400 000, increase. Considering the amount of fuel-related costs saved per operation day, for each of the solution types against their respective baselines, it is possible to estimate the amount of time it would take to recuperate the additional investment in the fleet - the *break even point*. An analysis was made in order to estimate the variation on the break even point if we cut the electric vehicle prices. Figure 6.5 shows its results. As it is possible to see, the break-even points for full-price electric vehicle fleets are longer than 100 years. In fact, the break even point lowers very slowly with the discount variation, still exceeding 30 years even with half-priced vehicles.

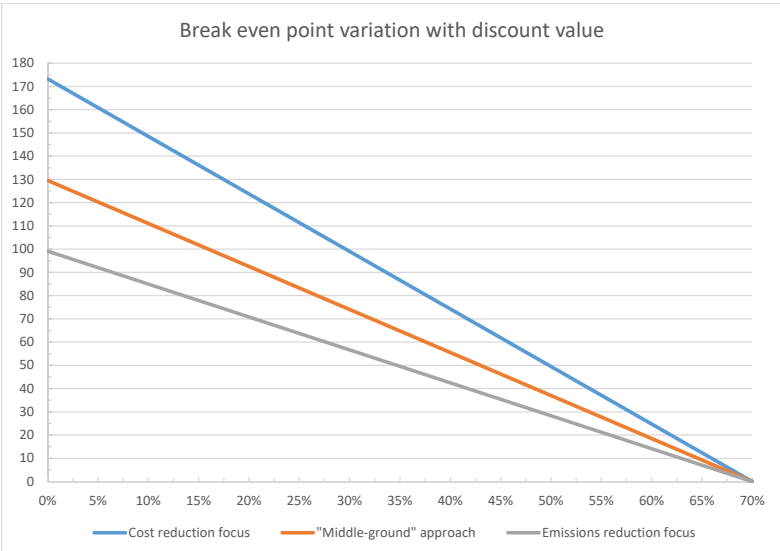


Figure 6.5: Break even analysis for different solution approaches.

6.4.3.6 Brief Sensitivity Analysis

Additional studies were made to the impact of electric vehicle autonomy and purchase costs on the break even point of investment.

1. **Autonomy increase analysis against a baseline fleet considering purchase costs in the evaluation function**

We first decided to see if extending the vehicle autonomy would translate into an increase of electric vehicles in the fleet, even when considering full purchase costs in the evaluation functions. The sensitivity analysis was performed on the extra battery percentage parameter, for a single operations day, 10/05/2016 (a Tuesday, assuming it to be a standard operational day in the week), so as to minimize the total run-time needed to gather all the data. The results were compared to the baseline fleet described in Paragraph 2 for the same day, consisting of 190 CNG buses and 167 diesel ones, totaling a fleet size of 357 vehicles. To reach our figures, the solver was executed considering an extra amount of electric bus autonomy up to +100%, in increments of 10%. A similar approach as before was used to determine the break even point. Figure 6.6 illustrates the results obtained for emission reduction favouring solutions. It is possible to conclude that, for an extra autonomy of 30%, we start seeing significant increases in the number of electric buses in the fleet which translate proportionately in reductions to the break even point. The sensitivity analysis on this parameter for total cost favoring solutions and median valued solutions did not show an increase in the number of electric vehicles in the fleet, in comparison to the baseline solutions. As such we could not analyze the break-even point for these solution typologies.

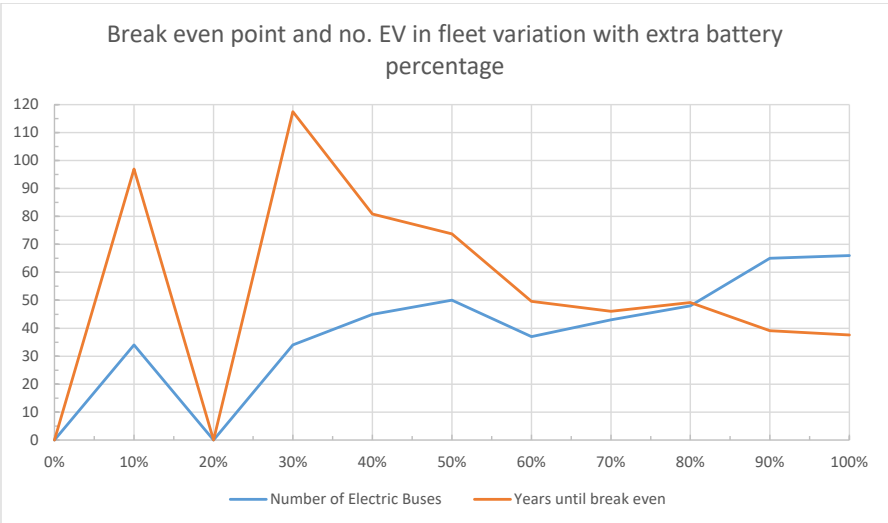


Figure 6.6: Break even and electric bus allocation analysis in relation to extra battery percentage. Notice the proportional reduction in years to reach the break even point to the number of electric vehicles in the fleet, for <30% extra battery.

2. **Autonomy increase analysis against a baseline fleet without considering purchase costs in the evaluation function**

Another sensitivity analysis was made not considering vehicle purchase costs initially in the solver's evaluation function, in a similar fashion to the study in Paragraph 2. Vehicle purchase costs were considered *a posteriori*, in order to promote an increase in the number of electric vehicles in the fleet, and properly analyze their impact in the break-even point. For this analysis, all three solution typologies obtained mixed fleet configurations with a balanced number of electric vehicles and thus were considered in this discussion. Figure 6.7 illustrates the obtained results, showing the connection of extra battery autonomy to the break-even point reduction. We can see that there

is a reduction in the break-even point as we extend the autonomy of the electric vehicles. The results are somewhat irregular for extra battery values lower than 30% but seem to stabilize after that value.

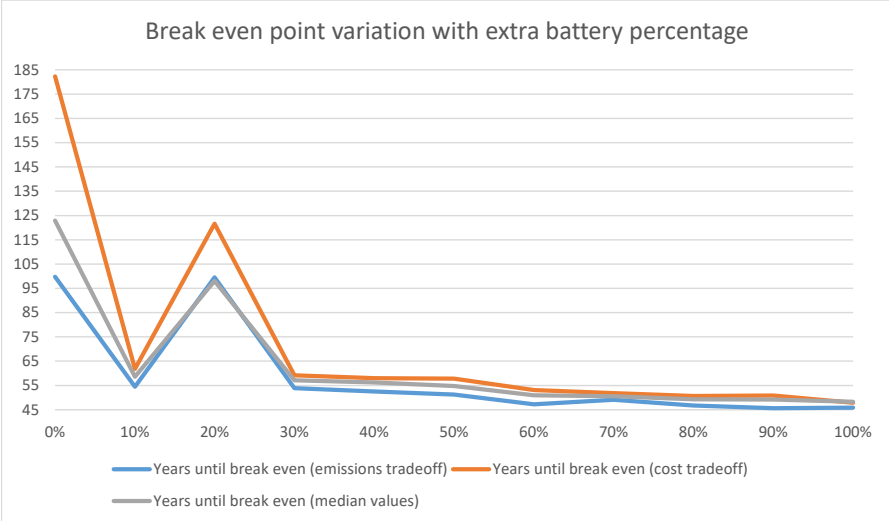


Figure 6.7: Break even analysis in relation to extra battery percentage, when vehicle purchase costs are not considered.

3. **Reducing electric vehicle purchase costs**

   Based on the previously analyzed values, we can study how decreasing the electric vehicle purchase costs could further lower our break-even point. For a 25% discount in electric vehicle purchase costs, we achieve a reduction of an average 20 years in the break-even point. For 50% and 70% discounts, this reduction is of an average 40 and 55 years, respectively.

Short Summary The case study describes the formalization of a mixed bus fleet management issue as a multi-objective, integer optimization problem. The implementation considers real-world operational data. A sensitivity analysis is performed on the variation of electric bus purchase costs and its autonomy. The results show us an overall improvement in pollutant emission and fuel cost reduction for fleets containing electric vehicles when compared to baseline fleets of the same solution typologies. However, it also shows the impact of the high electric bus purchase cost on the composition of the fleet and the respective break even point of investment, when these costs were directly considered by the solver. The sensitivity analysis indicates that if the EV purchase costs are reduced and the autonomy is increased, there are significant improvements in the fleet composition and break even point. In addition, it indicates that scaling the number of EVs in the fleet influences the break-even points positively. However, the magnitude of the purchase costs still prop the break even point of investment to undesirable amounts (over 10 years time). In this work we have considered neither the depreciation and maintenance costs (e.g. purchasing new batteries for the electric buses), nor the variations of the traffic flows in different traffic peak hours. As such, we will be addressing these issues in future analysis and research efforts following up this thesis.

6.4.4 Discover Driving Profiles in Electrified Public Transportation

In the previous subsection we simulated and analyzed the performance of a mixed fleet of buses from an investors perspective. In this case study we will focus on behavioral aspects of the driver (user) in terms of driving style. We propose the implementation of a clustering-based methodological approach for the identification of driving behaviors as a data-driven component of the *data & models engine* (*descriptive & predictive models*) depicted in Figure 6.2. The study can give transport operators with the resources they need to evaluate drivers and their energy performance. The results could enable fleet managers to develop and implement various operational plans while keeping in mind that improved driver performance leads to considerable gains not only in energy/fuel consumption, but also in the company's operating costs.

6.4.4.1 Objectives

In this case study is to answer the following question: *what are the existing profiles in terms within the group of professional bus drivers drivers?* For this purpose we consider descriptive modeling techniques as part of the framework described in section 6.3.2

Our methodological approach is based on the evidence accumulation concept proposed by [FJ05] and unfolds in four phases as depicted in Figure 6.8. The framework comprises the following four steps:i) ensemble clustering, ii) calculation of the optimal number of clusters, iii) co-association matrix computation, and iv)final clustering partition computation, which are detailed in the following subsections.

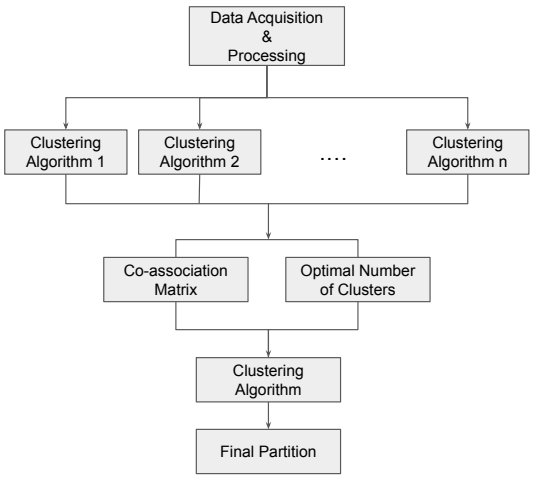


Figure 6.8: Flowchart to determine the clusters in the drivers data-set.

6.4.4.2 Ensemble Clustering

Let $X = \{x_1, x_2, \ldots, x_n\}$ be a set of data points with cardinality $|X|$ with x_i being defined over a d-dimensional feature space, $x_i \in R^d$. A clustering algorithm arranges the input data X into distinct patterns (k clusters) given some similarity measure between observations. The algorithm being applied to different clustering methods outputs a set of clustering partitions $\mathcal{C}$ with cardinality N:

$$\mathcal{C} = \{C^{(1)}, C^{(2)}, ..., C^{(N)}\} \tag{6.9}$$

where $C^{(N)} = \{c^{(1)}(x_1), c^{(2)}(x_2), ..., c^{(k)}(x_n)\}$ shows a partition from the Nth clustering algorithm, $c^{(k)}(x_i)$ denotes the label k the clustering algorithm has assigned to the x_i data point, and $X_k^{(N)}$ is the sample of data point grouped in cluster k by clustering algorithm N.

As stated in [FJ05], different clustering algorithms will, in general, produce different partitions for the same data set, either in terms of cluster membership and/or the number of clusters produced. Clustering ensembles can be generated by following two approaches: i) choice of data representation (i.e. ...) and ii) choice of clustering algorithms or algorithmic parameters. In this work, the second approach was followed using a number of well-known clustering algorithms and considering as parameters the numbers of k clusters and distinct distance metrics.

Optimal number of clusters The problem is to find an "optimal" data partition, C^*, using the information available in $\mathcal{C} = \{C^{(1)}, C^{(2)}, ..., C^{(N)}\}$. We define k^* as the number of clusters in C^*. To compute the k^* we need to reach a consensus among the partitions for different k number of clusters in $\mathcal{C}$. For this purposes we use the *Consensus Clustering* framework proposed in [VE09]. The framework defines a consensus index that quantifies the average agreement between all pairs of clustering solutions in a partition set $C_k = \{C_k^{(1)}, C_k^{(2)}, ..., C_k^{(B)}\}$ of B partitions of k clusters each, $C_k \subset \mathcal{C}$, as:

$$CI(C_k) = \sum_{i<j} SI(C_k^{(i)}, C_k^{(j)}) \tag{6.10}$$

where SI is a clustering similarity index used as agreement measure. The optimal number of clusters k^* is chosen as the one that maximizes CI:

$$k^* = \underset{k=2,...k_{max}}{\arg\max}\, CI(C_k) \tag{6.11}$$

For this work we use the *Adjusted Mutual Information* (AMI) as agreement measure [VEB10], which is defined as:

$$AMI((C_k^{(i)}, C_k^{(j)})) = \frac{MI((C_k^{(i)}, C_k^{(j)})) - E[MI((C_k^{(i)}, C_k^{(j)}))]}{\sqrt{H(C_k^{(i)})H(C_k^{(j)}))} - E[MI(C_k^{(i)}, C_k^{(j)})]} \tag{6.12}$$

where, $MI()$ is the mutual information index, $H()$ is the entropy, and $E[.]$ denotes the expected value.

6.4.4.3 Evidence Accumulation Clustering

In Evidence Accumulation (EA) [FJ02, FJ05], each clustering partition is mapped into a n x n *binary* symmetric matrix $\mathcal{M}$, where n is the number of samples in the dataset. The matrix for the k clustering partition can be regarded as component matrix defined as:

$$\mathcal{M}^k(x_i, x_j) = \begin{cases} 1, & \text{if } c^{(t)}(x_i) = c^{(t)}(x_j) \\ 0, & \text{otherwise} \end{cases} \tag{6.13}$$

That is, in these matrices, the value 1 denotes that the corresponding data pair (x_i, x_j) are partitioned into the same cluster with label t, while 0 denotes that they are assigned into different clusters.

The mean of all the component matrices is defined as a n x n co-association matrix CoM , which provides the pairwise correlations by simple the frequency with which the data pair (x_i, x_j) is assigned to the same cluster among the N partitions in $\mathcal{C}$. Formally the matrix is defined as:

$$CoM(x_i, x_j) = \frac{n_{ij}}{N} \tag{6.14}$$

Authors in [FJ02, FJ05] considered this average as a voting mechanism for combining the clustering results. The EA process transform the original d-dimensional feature space into a a new representation in form of a n x n affinity matrix. The underlying assumption is that patterns belonging to a "natural" cluster are very likely to be collocated in the same cluster in different data partitions.

Wang et al. extend the EAC concept and the resulting co-association matrix in [WYZ09] to account both for the clusters' size of each cluster, and the dimension of the observations. They define the component matrix for the k clustering partition as:

$$\mathcal{M}^k(x_i, x_j) = \begin{cases} 1, & \text{if } i = j, \\ 0, & \text{if } i \neq j, \\ \frac{1}{1+\sqrt[d]{|X_l^{(k)}|}}, & \text{if } c^{(t)}(x_i) = c^{(t)}(x_j) = l \end{cases} \tag{6.15}$$

where, l is the label from the *k-th* partition and d is the dimension of the features space.

The co-association matrix is computed as :

$$CoM = \sum_{k=1}^{N} \mathcal{M}^k \tag{6.16}$$

In this study we will use the co-association matrix in equation 6.16 as affinity matrix for the computation of the final clustering partition.

Computing Final Partition The idea of the last stage is to use the new data representation given by the co-association matrix and the optimal number of clusters computed by the ensemble clustering to recover the final clustering partition. We use the spectral clustering algorithm [NJW01].

Driving Profile Label Algorithm To define the driver profiles, we use the profile label algorithm (see Algorithm 1) proposed in [FAM+18]. The algorithm compares the median values for each variable of each cluster with a defined percentile of the distribution for the entire group data. The categories defined for the attributes are low, moderate, high and very high.

Algorithm 1: Driving Profile Label Algorithm (adapted from [FAM+18])

Input: Box-plot for $variable_i$ (i:1...n) in cluster, box-plot for all data for $variable_i$, list of percentiles $Percentile_k$, k:1..3

Output: $label_i$ of behavior for each variable

```
foreach variable, v_i, i:1...n do
    if Median(v_i) ≤ Percentile_1(AllDataForv_i) then
        label_i ← "Low"
    end
    else if Percentile_1(AllDataForv_i) < Median(v_i) ≤ Percentile_2(AllDataForv_i)
     then
        label_i ← "Moderate"
    end
    else if Percentile_2(AllDataForv_i) < Median(v_i) ≤ Percentile_3(AllDataForv_i)
     then
        label_i ← "High"
    end
    else if Median(v_i) > Percentile_3(AllDataForv_i) then
        label_i ← "VeryHigh"
    end
end
```

6.4.4.4 Experimental Setup and Results

We will apply the clustering methodological approach on the dataset described in section 6.4.2. For the purpose of finding driving profiles of eco-driving behaviors in electrified mobility, we will consider the following attributes: i) average speed, ii) number of excessive speed events per trip iii) average acceleration, iv) number of aggressive acceleration events per trip, v) average breaking, vi) number of aggressive breaking events per trip, vii) average energy consumption. To compute the profile labels we consider the 50 %, 75 %, and 90 % percentiles.

Settings for the Ensemble We consider the following clustering techniques to compute the ensemble and the affinity matrix: i) Hierarchical Clustering Approach (HCA) Single and Average Link [JD88] parametrized with different distance metrics, ii) k-means [SI84] using the *k-mean++* initialization approach [VA06], iii) Partitioning Around Medoids (PAM) [SR19], and iv) g-means [HE03]. These techniques resort to different measurements to define proximity between data instances resulting in different clusters, i.e. the data is grouped considering different characteristics.

Results The consensus index, defined in subsection 6.4.4.2, suggests that exist twelve clusters of potential driving profiles. Figure 6.9 shows the cluster characterisation using box plots. Figure 6.10 shows the values for each variable in the clusters against the median of all drivers. From the two figures we can observe that clusters one, five and eight have the most aggressive style than the other clusters, yet they present low average energy consumption. This happens because above a given speed the vehicle has gain the inertial forces and this is translated with low consumption. In the opposite directions moves cluster three that is characterized by high energy consumption and low speed profile. Cluster seven presents as well low energy consumption, however presents a moderate behaviour with respect to other driving characteristics. Clusters eleven and twelve exhibit a moderate driving style with somehow high average speeds but moderate average acceleration and breaking acceleration resulting into moderate to low energy consumption. All other clusters present a conservative driving behaviour characterized by low speed-related values.

Table 6.8 shows the clustered driving styles after we have applied Algorithm 1 to obtain the label for each variable. It is possible to identify 10 driving profiles because clusters two, four, and ten present the same label characterization. Table 6.9 presents the resulting profiles of diving behaviour. Now, profiles one, seven depict an aggressive driving style, accounting for almost the 9% of the population, while on the opposite side are profiles two, three and eight, with the least aggressive style, representing the almost 33% of the drivers. From an energy saving perspective profiles three and six have the highest consumption accounting for almost 27% of the drivers.In the table, we also show the number of drivers present in each group and their proportions in relation to the entire dataset.

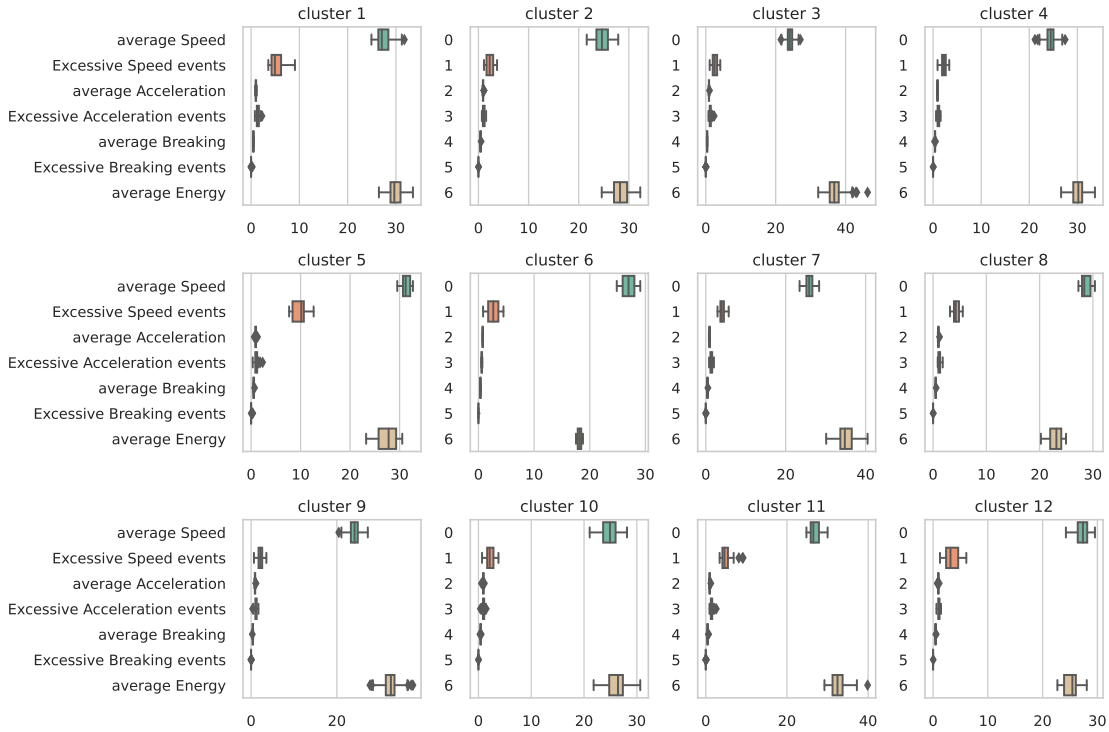


Figure 6.9: Driving Clusters

Cluster	Average Speed	Excessive Speed Events	Average Acceleration	Aggressive Acceleration Events	Average Breaking	Aggressive Breaking Events	Average Energy
1	High	High	High	High	High	Low	Low
2	Low	Low	Low	Low	Low	Low	Low
3	Low	Low	Low	Moderate	Low	Low	High
4	Low	Low	Low	Low	Low	Low	Low
5	Very High	Very High	Low	Low	Very High	Low	Low
6	High	Low	Low	Low	Low	Low	Low
7	Moderate	High	Moderate	Moderate	Moderate	Low	High
8	Very High	High	High	Low	Very High	Low	Low
9	Low	Low	Low	Low	Low	Low	Low
10	Low	Low	Low	Low	Low	Low	Low
11	High	High	Moderate	High	Moderate	Low	Moderate
12	High	Moderate	Moderate	Low	Moderate	Low	Low

Table 6.8: Driving styles clusters

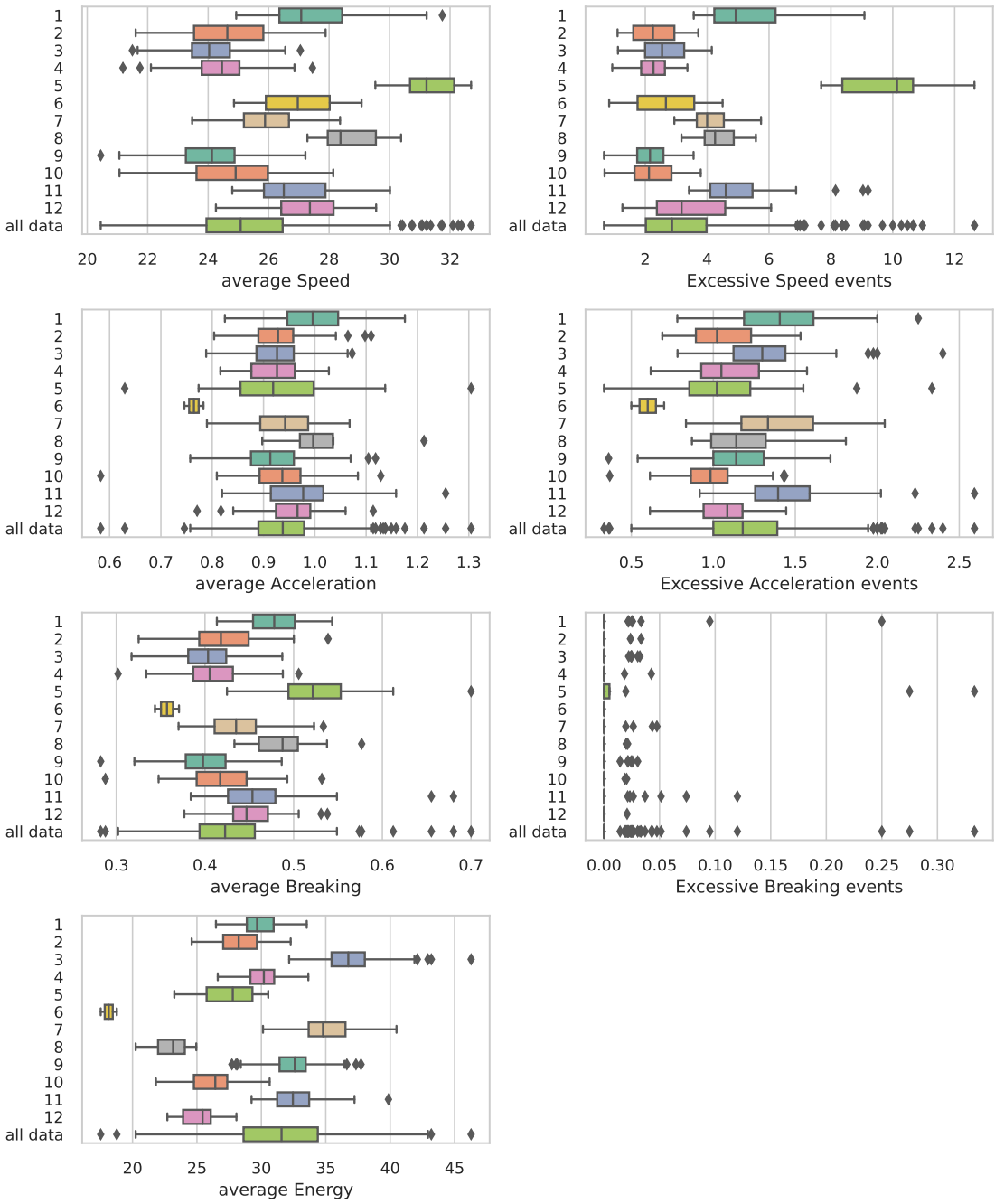


Figure 6.10: Comparing each variable with the median values found in the cluster.

Profile	Average Speed	Excessive Speed Events	Average Acceleration	Aggressive Acceleration Events	Average Breaking	Aggressive Breaking Events	Average Energy	N. of Drivers
1	High	High	High	High	High	Low	Low	55 (7.26%)
2	Low	Low	Low	Low	Low	Low	Low	209 (27.60%)
3	Low	Low	Low	Moderate	Low	Low	High	116 (15.35%)
4	Very High	Very High	Low	Low	Very High	Low	Low	12 (1.58%)
5	High	Low	Low	Low	Low	Low	Low	2 (0.26%)
6	Moderate	High	Moderate	Moderate	Moderate	Low	High	95 (12.55%)
7	Very High	High	High	Low	Very High	Low	Low	11 (1.45%)
8	Low	Low	Low	Low	Low	Low	Low	145 (19.15%)
9	High	High	Moderate	High	Moderate	Low	Moderate	70 (9.25%)
10	High	Moderate	Moderate	Low	Moderate	Low	Low	42 (5.55%)

Table 6.9: Driving profiles

Short Summary The study conducted can give bus company operators with the resources they need to evaluate drivers and their performance when driving various vehicles. The results enable fleet managers to develop and implement various operational plans and incentive schemes to promote safe and eco-driving behaviors as they affect both fuel/energy consumption and company's operating costs. The analysis identified 10 driving profiles. To achieve this result we investigated a dataset containing aggregate information of 757 drivers over one week data. The attributes we considered in the study were average speed, average acceleration/breaking, number of aggressive acceleration/breaking events, and average electric energy consumption. To the best of our knowledge, there are no clustering studies in the literature focusing on professional drivers in public transport with respect to driving behaviour considering energy consumption, even though some efforts may consider other techniques applied to the same application domain.

6.4.5 Behavioural Modeling for Policy Evaluation in Public Transportation

In traffic and transportation system analysis the way individuals make choices plays a paramount role as these will affect the general efficiency with which people can travel. Modifications on the system by means of policy intervention affect commuters' perspective impacting on the performance of the network and eventually on the society's welfare. The emergence of system's behaviour, as a result of decisions at individual level, provides the traffic manager with the opportunity to evaluate modifications that have been implemented on the system. However, there has been a slow advance in appropriately representing users and their behaviour in all social dimensions of intelligent transportation systems.

In this section we present the formalization of a methodological framework based on agent-based modelling, where we combine a macroscopic representation of the mobility domain with a microscopic resolution of commuters' decision-making processes. The purpose of the framework is to support traffic planners and managers in designing and evaluating ITS solutions and/or management policies. This case study is related to the *behavioural engine* proposed in Section 6.3.2 (*incentives* component). Results of this research were first reported in [KMR+14].

6.4.5.1 Conceptual Model for Policy Evaluation

Let's consider a mobility network with $m \in \mathbb{N}$mobility services and a population of $n \in \mathbb{N}$ commuters. Let $I = \{1, ..., n\}$ be the set of commuters travelling on the network and $S = \{1, ..., m\}$ the available mobility services. Let's consider the mobility network is represented by a directed graph (V, E) with node set V, link set $E \subseteq (V \times V)$, and k origin-destination pairs (o_i, d_i). Each link $e \in E$ represents a road segment and/or a public transport connection. Let $\mathcal{P}_i$ be the set of all paths connecting origin o_i to destination d_i. Let $\mathcal{P} = \cup_{i=1}^{k} \mathcal{P}_i$ be the set of all paths in the network.

There are a number of attributes that are associated with each link $e \in E$ such as capacity, $c_e \in \mathbb{R}_>0$, length, number of lanes, and the mode that characterises the link as being related to private, public, or mixed transport mode. A mobility service $j \in S$ from the other hand is characterized by the usage capacity $c_j \in \mathbb{N}$. In addition, to describe the congestion effects macroscopically, that is, how the exceeding capacity of flow in link e affects the time and speed of a travel, the network is endowed with a non-negative, non-decreasing latency function $\ell_e : \mathbb{N} \to \mathbb{R}_{\geq 0}$. The cost (delay) each commuter needs to support for travelling on path $p \in \mathcal{P}_{od}$ is:

$$\ell_p(x) = \sum_{e \in p} \ell_e(x_e) \tag{6.17}$$

where x_e is the flow on link e.

In this work we will use as latency function the well-known volume-delay function (see [dDOW11] denoted in equation 6.18.

$$t_e = t_{0e}[1 + \alpha(\frac{x_e}{c_e})^{\beta}] \tag{6.18}$$

Each commuter $i \in I$ wants to travel from an origin $o_i \in V$ to a destination $d_i \in V$. Each mobility service $j \in S$ is associated with a set of links. Let's define the set of commuters with same origin-destination as $I_m = \{i \in I | (o_i, d_i) = (o_m, d_m\}, m = 1, ..M$, where $M \in \mathbb{N}$ is the number of all possible origin-destination pairs. Let's denote t_{ij} a trip allocation binary variable defined as:

$$t_{ij} = \begin{cases} 1, & \text{if } i \in I \text{ travels on service } j \in S, \\ 0, & otherwise \end{cases} \tag{6.19}$$

The vector $\mathbf{a} = (a_{ij})_{i \in I, j \in Sn}$ is the mobility service allocation where commuters are represented with the mobility service they use . Considering the subset of commuters I_m traveling from origin o_m to destination d_m, we have the mobility service allocation for I_m, $\mathbf{a}_m = (a_{ij})_{i \in I_m, j \in S}$.

Commuters in the real system are described as an artificial society of agents,following the MAS paradigm, each of them characterised by a set of attributes regarding its travel preferences in terms of costs and time, and a set of socioeconomic features (e.g., income). From now on commuter and agent will be used interchangeably. Commuters make travel decisions daily based on their personal expectations and past travelling experiences. This acts as a memory where the commuter stores his travel experience. A generation module creates the demand to be assigned on the transportation network. Here, each commuter has an activity-based schedule, based on its own preferences and constraints, denoted with $\pi_i = (\theta_i, \hat{\theta}_i, \eta_{ij}, \delta_{ij})$, where $\theta_i, \hat{\theta}_i \in \mathbb{R}_{\geq 0}$ are the desired travel time and the delay tolerance, $\eta_{ij} \in \mathbb{N}$ is the preferred crowd level sharing the same mobility service j, and $\delta_{ij} \in \mathbb{R}_{\geq 0}$ is the the monetary value commuter i is willing to pay (or receive as reward) for using mobility service j. Each commuter makes travel decisions daily based on their personal

expectations and past travelling experiences.

The commuter decisions are based on the evaluation of their travel experience by means of a generalized utility function $\upsilon_i(\pi_i, \xi_i)$:

$$\upsilon_i^j(\xi_i) = \bar{\upsilon}_i - \phi_i^j(\pi_i, \xi_i)) + \lambda_i^j(\pi_i, \xi_i)) \tag{6.20}$$

where $\bar{\upsilon}_i^j$ represents a positive utility from performing the activity/travel using service $j \in S$, and functions ϕ_i^j and λ_i^j account for the costs (or disutility) and potential benefits respectively of using service j given the commuter's preferences π_i and observations $\xi_i = (\tilde{\theta_i}, \tilde{\eta_{ij}}, \tilde{\delta_{ij}})$, where $\theta_i \in \tilde{\mathbb{R}}_{\geq 0}$ is the experienced travel time, $\tilde{\eta_{ij}}$ is the observed number of co-travellers on service j, and $\tilde{\delta_{ij}}$ are the experienced costs or rewards, such as cost of travelling in terms of value-of-time, tolls/fares, crowd levels, incentives, and others.

For the following cases studies we adopt the utility functions in a similar way as in [GKN10]. We model the total utility of commuter's i decision using service j, as the sum of individual contributions as follows:

$$\upsilon^j = \sum_{k=1}^{n} \upsilon_{perf,k} + \sum_{k=1}^{n} \phi_{late,k}^j + \sum_{k=1}^{n} \phi_{cost,k}^j + \sum_{k=1}^{n} \phi_{social,k}^j \tag{6.21}$$

where υ^j is the total utility for a given plan, using service j; n is the number of activities, which equals the number of trips . $\upsilon_{pref,k}$ is the utility perceived for performing activity k; $\phi_{late,k}^j$ is the (negative) utility or cost for arriving late to activity k (it accounts for experienced travel and waiting time); $\phi_{cost,k}^j$ is the (negative) utility perceived for traveling during trip k; and $\phi_{social,k}^j$ represents social costs or benefits perceived by commuters during their travel activities in terms of crowdness levels.

6.4.5.2 Scenario: Study of Rush-Hour Avoidance

To illustrate the perspective of the conceptual framework in representing human behaviour (see subsection 6.4.5.1) we will consider a simple scenario on a bi-modal network as we have presented in [KMR+14, MRCK14].The mobility network is composed of two services, namely public (PT) and private (PR) (i.e. use of private car) transportation modes, where commuters need to make choices over mobility services and departure times. The example considers a simple network with a high morning peak-hour demand. Let us assume that a traffic planner wants to introduce a set of policy measures to alleviate traffic conditions during such an interval. In this context we evaluate the effects of two types of interventions: i) market and ii) incentive-based policies. The former operates on the monetary costs (i.e. prices) the commuters are charged for their travel activities, while the latter uses a reward to achieve the desired behavioural shift. During the evaluation of the policy application we look not only at time and monetary costs, but also we account for the social cost/benefits commuters individually perceive. For the present example, we consider as social factors the level of crowding and perceived comfort in the PT mode, and the level of emissions in

the PR mode.

Network: The scenario consists of a bi-modal network with one origin o and one destination d nodes, and two possible mobility services between them. For the sake of simplicity, we assume there exist two paths connecting the (o, d) pair both composed of one-way links with different capacities, and each path is dedicated to one mode only, either private or public transport. Each link e is characterised by a length l_e (in kilometers) and a capacity c_e (in vehicles/h). This setting resembles the peak-avoidance experiment depicted in [BEE09].

Commuters decision model: For each commuter a number of state variables are defined such as: i) desired departure and arrival times; ii) experienced travel time; iii) the uncertainty they experienced during the trip with a given transportation mode; iv) a set of preferences about the transportation mode; v) the perceived comfort as personal satisfaction for the mode choice; and vi) a daily income variable. While the agent experience its travel activities, the costs associated with the different transportation modes, the perceived satisfaction of travelling and (potential) rewards the mode and time choices. Commuters can choose between travelling by PT or PR modes based on the own-car value. The decision-making process of each agent is assumed to maximise the utility and flow equilibrium on roads. They perceive current traffic condition as well as previous experience and use this information in making other decisions.

With regard to the utility equation as defined in 6.21, the utility of public and private modes can be measured as follows:

$$\upsilon_{PR} = \sum_{k=1}^{n} \upsilon_{PR}^{k} \tag{6.22}$$

where k is the number of trips/activities, and υ_{pr}^{k} is the instantiation for the private mode.

$$\begin{aligned} \upsilon_{PR}^{k} = \alpha_{late_{PR}} \cdot (t_{tt,exp}^{k} - t_{tt}^{k}) \\ + \beta_{cost_{PR}} \cdot \frac{cost_{PR}}{income}) \\ + \alpha_{pollution} \cdot t_{tt}^{k} \cdot pollution \end{aligned} \tag{6.23}$$

where k is the number of trips/activities, and υ_{pr}^{k} is the instantiation for a public mobility service.

$$\upsilon_{PT} = \sum_{k=1}^{n} \upsilon_{PT}^{k} \tag{6.24}$$

$$
\begin{aligned}
v_{PT}^{k} = \alpha_{late_{PT}} \cdot (t_{tt,exp}^{k} - t_{tt}^{k}) \\
+ \beta_{cost_{PT}} \cdot \frac{cost_{PT}}{income}) \\
+ \alpha_{crowd_{PT}} \cdot \frac{\eta}{bus_{capacity}} \cdot t_{tt}^{k}
\end{aligned}
\tag{6.25}
$$

where t_{tt}^{k} and $t_{tt,exp}^{k}$ are total travel time and expected total travel time of trip k, $cost_{PR}$ is the monetary cost of private transportation (fuel, tolls, etc), $cost_{PT}$ is the fare of public transportation, *income* is the agent's income per day, *pollution* is the amount of pollution produced by private vehicles, $capacity_{exp}^{k}$ and $bus_{capacity}$ are expected capacity of bus and total capacity of each bus respectively, $t_{wt,exp}^{k}$ is the expected waiting time and t_{wt}^{k} is the waiting time during trip k. α_{late}, β_{PT}, β_{PR}, $\alpha_{pollution}$, $\alpha_{com_{PR}}$, $\alpha_{com_{PT}}$, and α_{cap} are considered as marginal utilities or preferences for different components.

Initial Setup: The scenario reflects a typical daily trip from a home to a work location. A three-hour morning commuting period is modelled from 7.30 am until 10.30 am. In this interval of time, it is observed a high demand, with a peak between 8.30 am and 10.00 am, on the PR path, where the utilisation of the route reaches the highest occupation. A synthetic population consisting of 2,500 agents has been created, in which each agent is characterised by a number of attributes denoting departure and arrival times, mode preferences, as well as some other socioeconomic features, such as its monthly income. Each agent has an initial activity-travel schedule that considers expected departure and arrival travel times. The travel times are assumed to follow a normal distribution that results in a rush peak-hour between 8.30 am and 10.00 am. The agent has two variables related to the mode choice capacity: car-ownership and flexibility. Car-ownership is a Boolean variable and indicates if the agent is private or public transportation user (we do not consider other type of modes, e.g. walking). Flexibility reflects the willingness of a private mode user to change to the public transportation. Thus, all agents in the scenario start their trip at origin o, between 07.30 am and 10.30 am. The paths between the pair (o, d) have both a length of 19 km. The free-flow travel time from origin node o to destination node d is roughly 25 minutes by car in the PR mode. For the public transportation, we consider the travel time from home to work to be around 33 minutes plus the waiting time at the bus stop. The bus frequency service is 10 minutes before the rush hour and 5 minutes during the rush hour (for the test set-up, 8.30 am - 9.30 am). The network is also evaluated by means of the average travel speed and the average travel time being stored for future comparisons.

Market-Based and Reward-Based Policies: We consider five simple policy interventions: three market-based, in which we consider an increase on the prices, and two reward-based, in which the authorities incentive the adoption of a temporal shift in the departure time. We are interested in analysing the impacts of prices vs temporal-shift incentives. The objective of the policy-making is to attenuate demand peak in rush hours. Therefore, market-based policies will consider:

- an increase in PR transportation (Policy 1), through increasing private costs (e.g. tolls, fuel, etc.);

- a decrease in public transportation (Policy 2), through reducing fares;
- a mixed policy (Policy 3), through decreasing fares and increasing PR costs.

We also considered two departure-time oriented policies where commuters are incentivized to shift their departure preferences:

- a departure-time incentive for all the commuters (Policy 4), as each commuter is rewarded with 2.00 monetary units before the rush hour and 1.00 monetary units after the rush hour.

Preliminary Simulation Results: We first consider a "baseline" scenario where no policy intervention is applied. We perform a preparatory run of the model so as a one-month simulation is considered (i.e. 30 iterations of the morning rush hours). This serves to establish the ratio of commuters distributed between the two modes along the departure time interval. We can consider that during this period agents "adapt" to make the choice that maximizes their utility. During the execution of the scenario, we monitor agents' utilities, travel times, the ratio of expected travel time and the observed travel time $\frac{tt_exp}{tt_obs}$ (for the private mode) and crowdness level for the public service. After this warm-up, a policy is introduced and the model is executed for another 30 iterations, i.e. another month, starting from the final iteration of the baseline scenario. In the market-based Policy 1, we can see, compared to the baseline scenario, an increase of commuters in 7.5% in the PT mode (see Table 6.10) and a decrease of commuters of 9.34% in PR mode (see Table 6.11). The social effects of a change in prices, on the one hand, is when PR costs increase – commuters who have changed from PR to PT are the commuters who cannot afford paying the new prices. We can see then the effect on the average expected utility in PR that increases by 2.8%. Agents who stay in PR mode are not influenced by the prices though. On the other hand, because the PT supply does not change, there is a 5% lost in expected utility in PT, which is explained by a rise in the average crowding by 5%.

Table 6.10: Public transportation insights

	Commuters Ratio	Average Travel Time [min]	Average Utility	Average Crowding
Baseline	55.4%	36.67	11.11	0.81
Policy 1	7.50%	-0.56%	-4.97%	5.06%
Policy 2	6.28%	-0.30%	-0.81%	3.20%
Policy 3	6.49%	-0.61%	-1.45%	3.97%
Policy 4	6.93%	-0.43%	-3.90%	2.24%
Policy 5	6.64%	-0.36%	-3.82%	2.70%

Table 6.11: Private transportation insights

	Commuters Ratio	Average Travel Time [min]	Average Utility	TTExp/TTObs	Average Pollution
Baseline	44.6%	25.24	17.60	1.05	5.05
Policy 1	-9.34%	-0.30%	2.76%	-18.89%	-0.30%
Policy 2	-7.81%	-0.26%	1.16%	0.39%	-0.26%
Policy 3	-8.08%	-0.29%	1.78%	-19.74%	-0.29%
Policy 4	-8.62%	0.38%	4.77%	0.22%	0.38%
Policy 5	-8.26%	0.90%	2.65%	-6.38%	0.90%

If we compare these results with Policy 2, we can see the PT expected utility drops by 1% and there is a rise in PT ratio of 6.28%. Therefore, PT commuters are somehow rewarded with a ticket price reduction and their utility does not drop as much as in Policy 1. At the same time, there is a rise in PR average utility because the network becomes less crowded. The results from the incentive-based policies need a different analysis, because there is not an increase effect on prices but rather the inverse effect, i.e. a subsidisation. At the same time, the incentive seeks to approximate PR costs to PT costs by a 2.00 monetary units subsidy before rush hour and 1.00 monetary units after rush hour. More, the objective of those incentives in theory is not to achieve mode shift but rather to flat demand. However, results suggest a different perspective. In a modal shift perspective there is a rise of 7% (Policy 4) and 6.7% (Policy 5) in modal shift. This modal shift is not explained only by the effect of the subsidisation *per se*. It also occurs because among all agents that have travelled before the rush hours, some have decided to change their mode to PT in expectation to achieve higher utilities. Another point that emerges from the results is that the shift in departure time, obtained applying incentive-based policies, gives a similar effect of the Braess' paradox [BNW05]. Here we verify congestion effects not on a route-choice but rather on a time-choice basis (see Fig. 6.11).

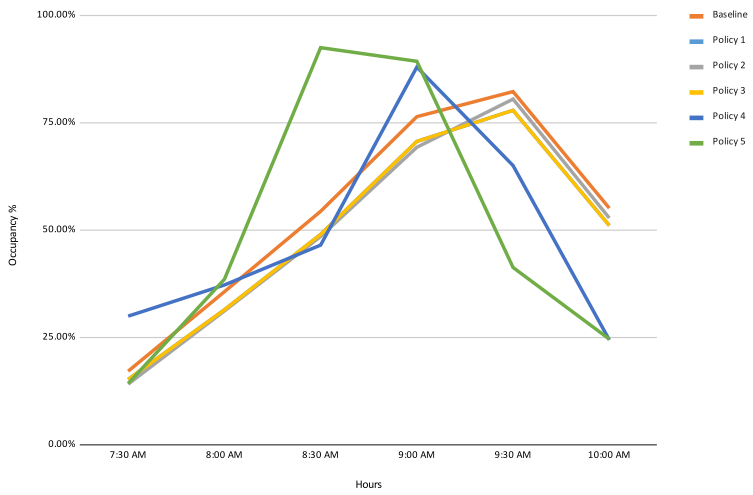


Figure 6.11: Average commuters on car under different policies

The results of this preliminary analysis suggest that transportation planners should anticipate both positive and negative effects of their strategies, by means of either market-based or incentive-based policies. Thus, behavioural shift in mode choice needs to be followed by proper investments (i.e. encouraging the usage of public transportation can succeed only if it is followed by an improvement at infrastructure and quality of service levels).

Short Summary We presented the formalization of a methodological framework based on agent-based modelling, where we combine a macroscopic representation of the mobility domain with a microscopic resolution of commuters' decision-making processes. The purpose of the framework is to support traffic planners and managers in designing and evaluating ITS solutions and/or management policies. To illustrate the viability of our approach in representing human behaviour, we built a synthetic population of adaptive com-

muters, where each of them implements a memory to keep travel experiences. We can thus conduct the within-to-day and day-to-day transportation and traffic analysis considering behavioural and social aspects of commuters based on their preferences. From the preliminary illustrative example, we can conclude that transportation planners should anticipate both positive and negative effects of their strategies, by means of either market-based or incentive-based policies. Thus, if we want to encourage the use of public transportation instead of using private vehicles we need to plan for the emergence of perverse incentives that can backfire our policies, as it is the case of applying discounts on fares without improving both the infrastructure and the supply in terms of higher frequency/capacity trips. What we will be likely observing is a great behavioural shift in mode choice (from private to public mode), as soon as the incentive process begins, with the tendency of returning to the initial conditions because of poor perceived quality of service levels over time.

6.5 Summary

In this chapter we illustrate the conceptualization of a decision-support framework is conceived to support the evaluation of actionable policies to yield social coordination exploring the concept of climate intelligence to leverage sustainability in domains where resources are competed by the different actors. The platform includes model-driven and data-driven methodologies for both generating and analyzing insights that can be used to enable actions towards the planning of operations at different levels, operational , tactical, and strategic. The gamification and incentive designs components, part of the *behavioural engine* aim to provide a two-way, two-fold interaction channel. From one hand they serve as a user-centric data generator, where relevant information can be gathered related to users' preferences and behaviours, and from the other, customized insights, recommendations, and rewards can be offered to users' for having aligned with the goals of the system. To showcase the framework we present several methodological approaches as case studies in public transportation that implement different elements of the framework, namely: a) a digital twin capable of assessing operational policies in electrified public transportation, b) a formalization of the mixed bus fleet management problem as a multi-objective integer optimization problem where we used it to perform an econometric analysis of the investment perspective to substitute internal combustion engine buses with electric ones, c) a clustering methodological approach to enable fleet managers to develop and implement various operational plans to evaluate drivers and their energy-profile performance, and d) a formalization of a methodological framework based on agent-based modelling for supporting traffic planners and managers in designing and evaluating ITS solutions and/or management policies.

Chapter 7

Conclusions

Competitive and dynamic environments are perfect reflections of the openness and "selfishness" exposed in open multi-agent systems; an unknown population of heterogeneous entities, each of them competing for resources and pursuing their own goals while they can join or exit the system at any time, and in which there is no direct control on their behaviors. They make autonomous decisions about the plans they will perform, learning from their previous experiences and influencing each other in both positive and negative ways. The cross-fertilization observed among MAS, market structures and incentive artifacts is strong where each can contribute to the advancement of the other.

A well known problem in the traffic and transportation domains is the allocation of resources in equilibria that does not represent equity, fairness, and safety among the commuters. Searching for a "pure" solution is rather a utopia due to both human nature and existing settings in many sites of the world. Thus the proposed approach in this thesis can offer solutions to a problem that needs strong assumptions about the environment. However, transcending this rationale we believe we can discuss a viable approach that brings the traffic and transportation systems into the implementation of social aware solutions. The aim of incentive mechanisms is to leverage the coordination among independent self-interested entities towards a sustainable system operation. As such, the proposed work in this document follows the identified research stream aiming at the specification and implementation of a conceptual framework where traffic management can be tested and evaluated in their application by incentivizing shifts in agents' behavior towards a social-aware utilization of the system's resources. This framework is based on the integration of a traffic microscopic simulation and a multi-agent system as a means to build an artificial laboratory for simulating a society of driver-agents, implementing their own decision-making capabilities, immersed in a urban traffic scenario. Additional contributions naturally arise from this research work, representing opportunities for further investigation (and practical applications) of the incentive mechanisms from the "behavior assimilation" point of view and "behavior persuasion" in MAS perspective.

This thesis studies and explores the applicability of incentive mechanisms as a social coordination method (towards social welfare) in MASs operating in dynamic and competitive environments. This thesis is primarily inspired by traffic and transportation networks, as well as energy markets. These two areas may be conceptualized as MASs functioning in dynamic and competitive contexts.

7.1 Main Contributions

We have started by considering the transportation domain and in particular way the Intelligent Transportation System area. We show the use of the agent-based technology considering its dual nature, as both a modelling and a programming paradigm. This way we can use MASs to design incentive schemes and assessing different policies. As a modeling paradigm supporting system engineering, we use agents to represent a society where the introduction of an incentive or policy can be assessed before its actual deployment on a given system.

We have introduce the "problem" of (public) policy making and show through the literature review how and why agents can provide support in the decision-making throughout all the stages of the policy definition. Our focus is on how to devise and evaluate incentive-based policies. Thus we introduced briefly the incentive theory as it is defined in the economics domain. We presented how policy-making and incentives are seen in the transportation domain and how agent-based modelling and simulation has been used as an evaluation tool. Finally we considered the way the MAS community has employed the incentive-based mechanisms in various competitive domains. There are several mechanisms available, such as game theory, market-based structures and auctions, contract theory and norms, trust and reputation based approaches that can be employed to achieve coordination. Furthermore, coordination itself is manifold and its appropriate form depends on the nature of the problem we study. It can be either *resource-oriented* or t*ask-oriented*. On a different dimension, coordination can be *collaborative* or *competitive*. Reviewing the literature we saw that different techniques fit into different coordination problems. Throughout the chapters of this thesis, we put focus on how coordination mechanisms, either as direct incentive scheme or as result of a policy, affect *social welfare*, having in mind that social welfare may not always align with the global optimum that the system desires to achieve.

Following, we will revisit the research questions formulated in Section 1.2 and describe the methods we used to address them, resulting in the key contributions of this dissertation.

The first question was formulated in Chapter 1, as follows.

1. *Are market structures efficient enablers for achieving social coordination in Multi-Agent Systems?*

Given the increasing importance of market-based settings in many situations, innovative techniques such as autonomous and automatic decision-making systems will be required. We examined modern information systems that give expanded capabilities to assist both the system and market operations for increasing the system's observability and controllability. The expansion of technological paradigms enables the implementation of market-oriented initiatives for more efficient supply and demand management. This possibility has fostered the emergence of new "side-market" structures, characterized by variable volatility and ephemeral existence, operating in parallel with traditional markets within a given system. Following an overview of the potential market structures, exemplified in the case of the electricity market yet present in other systems, our objective is to formalize the elements that frame and characterize their interactions.

To address the research question we have followed three steps. First, a holistic view of market structures and the way they interact was presented. Then, a system where this view can be materialized was conceptualised. Finally, we assessed our approach through simulation, showing the benefit of adopting market structures on achieving social coordination.

To accomplish the first step we have presented ResMAS. It consists of a meta-model of resource-based markets, based on the MAS paradigm, conceived to support the implementation, assessment and deployment of different soft regulation policies (incentive designs). It was conceived as a means for controlling unbalanced demand, resource allocation, or market failures while managing to promote social coordination in energy systems.

We need to understand how different market structures interact with the whole system. Market failures can emerge due to competitive behaviors or other exogenous factors. The integration becomes more crucial when decentralized and deregulated emerging markets are considered, such as peer-to-peer and virtual markets. Indeed, a model that discusses how different markets of the same domain interact and analyses the impact of participation in multiple markets, had not been previously fully considered in the literature.

To assess the applicability of ResMAS, we have considered a case study of a Home Energy Management (HEM) system. HEMs have been suggested as a solution to monitor real-time consumption and to schedule appliance operations according to specific user-defined criteria. From the demand-side perspective, implementing such a system implies selecting a scheduling technique to find timing for the household appliances. Distributed DSM techniques emerge as a plausible alternative to traditional ones. In our study, HEM agents are in control of specific appliances and schedule their operation by negotiating with a *resource* agent, achieving coordination in the energy usage. We have formalized a mathematical model of a market structure based on ResMAS as an enabler for control and usage coordination of the shared resources. Within this structure, agents tailor the optimization criteria. We consider the environment is composed of two market structures: the first is characterized as a tariff-based and is where the HEM agents purchase resource instances from the suppliers; and, the second is a proposal-based market where appliance scheduler agents engage in negotiations with the HEM agent leading to a schedule of energy consumption for each appliance.

Finally, simulation results on a *bill regulation* (cost-based regulation policy) scenario have shown evidences that it is possible to achieve a power consumption profile with low energy consumption and daily costs, maintaining good satisfaction levels that translate in improving the social welfare of the home ecosystem.

The second research question was proposed as follows.

2. *Can a voting strategy be used to yield social welfare?*

To deal with this research question we have considered analyzing collective decision-making in traffic applications and specifically in the context of CAVs in platoon formations. In recent years, the relevance of platooning has increased and it is considered promising in terms of road safety, utilization, and reduction of fuel consumption [DCM+18]. MAS research has considered elections through voting as collective decision-making mechanisms to reach consensus over the agents' aggregated preferences. It is reasonable to weigh

applying voting in traffic when groups of participants need to agree on a common goal.

Our approach to addressing this research question is three-fold. While our objective is to propose computational social choice mechanisms for establishing cooperative behavior within traffic scenarios involving autonomous vehicles, we argue that the evaluation of such collective decision-making should consider realistic constraints of the environment. Therefore, we have implemented a simulation framework to validate MAS-based coordination mechanisms for CAVs. The framework in question has to provide a vehicular traffic simulator environment that allows for near real-world modeling of constraints within vehicular networks (both at the kinematic and network-level) and endows each vehicle with high-level decision-making cognitive capabilities.

In the second stage, the framework used a scenario of lane-merging for platoon formation as benchmark. The set-up considers a bargaining mechanism as a negotiation approach between CAVs. The experimental results showed that the framework scales well up to 1000 vehicles with room for improvement.

Finally, we formalized the coordination of autonomous vehicles in platoon formation based on voting mechanisms. We focused on single-winner voting rules with an iterative process to reach a consensus on a platoon's cruising speed, assuming an initial platoon formation and single-round committee voting to agree on the route. We used the simulation framework to analyze the effect of the voting mechanisms on the platoon formation from the time-to-consensus metric perspective, and on the social welfare function, as a performance metric of the coordination.

We formulated the third research question as follows.

3. *Can auction methods be used to yield social welfare?*

In order to address this research question, we applied iterative auction-based incentive designs for establishing social coordination in platoon scenarios involving autonomous vehicles. Our objective was to show the suitability of well-known auction rules for tactical-level collective decision-making in platooning applications by comparing two auction rules as proof of concept: first- and second-price sealed-bid auctions. We evaluated the impact of the auction rules on the quantities of monetary flows, platoon welfare from utilitarian and egalitarian perspectives (measured in average and minimum utility), and time to consensus. As a concrete scenario, we considered an already formed platoon whose members needed to agree on two contexts: cruising speed and route. Each platoon member has a preference for speed levels and routes for an origin-destination pair, a willingness-to-pay preference for each resource, and an endowment that reflects the available monetary units. For the route choice each platoon member considers the sequences of vertices representing the preferred and the alternative routes. We used the Hamming distance to measure the similarity between these two routes and compare it with the desired maximum similarity to compute the utility for the routing context.

When constructing an auctioning mechanism for real-world deployment, it is important to consider the non-negligible communication delay that exists. The induced latency at the size assessed (auction groups of 8 or fewer members) is far below the time constraints for tactical level decision-making (less than 2 seconds). However, it appears that the time to

consensus grows exponentially with size, making large-scale implementation in the actual world impractical.

The results on platoon welfare show very small differences between the first-price and second-price rules. At small platoon sizes the first-price rule grants higher welfare from an utilitarian and egalitarian perspective, however welfare differences between the two quickly become insignificant as the size of the platoon increases. As such the second-price rule is more beneficial, as at a very small cost to welfare, the benefit of enforcing truthfulness can be obtained.

The platoon welfare results show minor differences between the first and second-price rules. When platoon sizes are small, the first-price rule provides more welfare from both a utilitarian and egalitarian standpoint. However, as platoon sizes grow, the welfare differences between the two become insignificant. As a result, the second-price rule is more advantageous due to enforcing truthfulness, at a low cost, resulting in a more "genuine" welfare distribution.

Finally, the last research question considers social welfare and coordination from a system point of view, and was formulated as follows.

4. *Is social welfare a good metric to evaluate actionable policies towards the implementation of sustainable systems?*

To address this research question, we illustrate the conceptualization of a decision-support framework meant to support the evaluation of actionable policies to yield social coordination. The proposed framework explores the concept of climate intelligence to leverage sustainability in domains where resources are competed by the different actors. The platform includes model-driven and data-driven methodologies for both generating and analyzing insights that can be used to enable actions towards the planning of operations at different levels, namely operational, tactical, and strategic. The gamification and incentive designs components, part of the *behavioral engine* aim to provide a two-way, two-fold interaction channel. On the one hand, they serve as a user-centric data generator, where relevant information can be gathered related to users' preferences and behaviors. On the other hand, customized insights, recommendations, and rewards can be offered to users so as to allow for aligned goals of the users and of the system. To showcase the framework we present several methodological approaches as case studies in public transportation that implement different elements of the framework, namely: a) a simulation model capable of assessing operational policies in electrified public transportation; b) a formalization of the mixed bus fleet management problem as a multi-objective integer optimization problem, where we used it to perform an econometric analysis of the investment perspective to substitute internal combustion engine buses with electric ones; c) a clustering methodological approach to enable fleet managers to develop and implement various operational plans to evaluate drivers and their energy-profile performance; and, d) a formalization of a methodological framework based on agent-based modelling for supporting traffic planners and managers in designing and evaluating ITS solutions and/or management policies. The conclusion we can draw addressing the research question is that albeit social welfare appears to be a good metric to evaluate actionable policies (towards the implementation of sustainable systems), it is not sufficient alone to yield such desired effect as it does not guarantee the system's sustainability along all dimensions namely economic, social, and environmental.

It needs to be supported by other performance indicators properly selected for the such a purpose.

Additionally to addressing the proposed research questions, it is necessary to account for whether or not the thesis' hypothesis hold given the obtained results. First and foremost, let us recall our hypothesis, which is formulated as follows.

> *Introducing incentive designs in dynamic and competitive environments leverages the system propensity to yield social coordination among agents.*

This statement appears to be intuitive. Nonetheless, throughout this dissertation we have explored incentive designs and coordination policies from different facets. We showed there are several approaches available to implement incentive designs and policies, such as auctions, market structures, gamification, and computational social choice techniques. We were particularly focused on understanding how such approaches affect "social welfare" as a metric of social coordination and assess their effectiveness. Therefore, the hypothesis holds within the boundaries of our experimental frameworks.

7.2 Further Developments

The approaches explored in this dissertation allow the design of incentive policies for achieving social coordination in dynamic and competitive systems. We are able to suggest they can promote the social welfare of agent societies within the boundaries of the experimental set-ups within which they have been considered. However, we reckon further developments are necessary to enhance the generalization of each approach presented in this doctoral research, as we discuss next.

- With respect to market-based structures as coordination enablers, future developments include:
  - **New regulation mechanisms.** Exploring further the modeling capabilities of ResMAS opens up the possibility of including new regulation mechanisms in two levels: market regulations and agent regulation. We intend to extend ResMAS in the context of regulation-aware agents, creating new demand-side management and agent decision processes that consider incentive mechanisms, such as dynamic pricing and mechanism designs that both improve coordination and promote beneficial behaviors avoiding system failures.
  - **Application of ResMAS to other domains.** The idea of introducing market mechanisms in transportation is not new (e.g. tolling systems). Authors in [CGO18, BGR+20] discuss the drawbacks of current mechanisms and suggest the introduction of market designs similar to the electricity market structures and their mechanisms to overcome the current limitations. We believe ResMAS, with its "holistic" view of multi-resource (multi-commodity) markets, has rich semantics which turn it into a proper and sound methodology to formalize and develop market designs for the integrated transportation domains.

- **Improvements in HEM agents.** Agents in the HEM case study demonstrated a straightforward decision-making process based on their present information. Furthermore, the HEM Agent will be enhanced in the future by incorporating Machine Learning algorithms to forecast the power generated by renewable sources.

- With respect to coordination of autonomous vehicles, future developments include:

  - **Improvements on the flexibility of the simulation platform.** The optimization and refinement of the architecture can lead to reduced processing times and improve usability. In addition, the portability of the (LightJason) server component could be improved to facilitate the integration with other simulation frameworks.

  - **Improve experimental setup.** Different and more complex scenarios could be studied, including, but not limited to, other collective decision-making methods, such as *argumentation-based agreement* or *game-theoretic approaches*. Such new scenarios could include, for instance, platoon formation with slots assigned to vehicles according to given criteria, analysis of grouping or coalition formation algorithms, or other problems such as ramp-metering, intersection management, and ride-sharing, and so forth and so on.

  - **Switch coordination context.** We have discussed three different coordination approaches so far applied to platoon formations. However, there exist diverse coordination issues that necessitate appropriate approaches considering different degrees of autonomy and decision-making horizons. The ability to dynamically switch from one type of coordination mechanism to another, upon changing conditions, is one paramount property to bear in mind in future implementations.

  - **Agent behaviors.** A comprehensive investigation of agent behavior has to be carried out. The agent and mechanism models are simple, merely scratching the surface of the myriad intricacies of voting, auctions, and MAS. Malicious agents, as well as the manipulation of auctions and elections, have not been considered as yet. Such research will investigate and compare alternative techniques to mitigate these issues while maintaining good communication. Such study, however, would rely on communication protocol advances to ensure minimal latency. Moreover, it is important to consider that agents can represent humans to better assess policies in situation where human drivers coexist with autonomous vehicles.

  - **High-level communication.** A possible venue for future improvement is the development of a high-level language for the formation and adaptation of platoons, using vehicular communication standards, similar to [SARO14].

  - **Voting rules.** In this study we have considered a small number of existing voting rules with a simple iterative version. As future development we can consider more advanced iterative voting mechanisms in which strategic behaviors tend to manipulate the process. For example, in [KX21] authors discuss the dynamic

price of anarchy as the difference in social welfare between the truthful and worst-case equilibrium profiles resulting from repeated strategic manipulations. Since V2V applications are prone to adversarial behaviors, considerations on robust voting protocols will be beneficial for the system. In this dissertation, the voting rules have been used for reaching consensus on sequential allocation of platoon properties (i.e., speed, route). Nonetheless, it might be useful to consider the application of combinatorial voting rules, for instance ([CELM07]).

- **Analysis of auction.** In section 5.4.1 we have presented an iterative auction protocol. Future work should show formally the robustness of the protocol and how it manages to maintain coherent and consistent platoon formations. Generalizing the analysis to other dynamics, utility functions, or families of preference distributions are interesting and important directions for future work as well. Similarly to the considerations made for the voting mechanisms, it might be useful to consider the application of combinatorial auctions as well ([LSG+20]).

- **Distribution of payments.** Any given winner agent will have negative revenue unless the bidder loses multiple auctions. Consequently, it would not be wise of an agent to constantly bid in an attempt at winning every auction. As for the current approach to payment distribution, it uses the value an agent ascribes to a given resource as the main factor influencing the bids. However, richer vehicles may always bid higher and buy priority on imposing their preference over the others, while poorer vehicles risk starvation. This issue needs to be considered devising proper regulations to avoid situations of "exclusion." Additionally, future research will look into other potential factors affecting payment distributions, such as fuel losses incurred due to leading the platoon or due to performing maneuvers.

- **autonomous and human-driven vehicle scenarios.** It would be interesting to assess the coordination among autonomous vehicles with different autonomy levels and human drivers. More specifically, studding the subjectivity associated with the drivers' behaviour and its influence in mixed scenarios involving autonomous and human-driven vehicles is an important research line to be pursued.

- With respect to CI, future developments include:

  Improve CI platform. Although the experimental setups presented in Chapter 6 are standalone instances of a CI conceptualization, we are aware of the fact that in its current form it cannot be used to provide useful recommendations of actionable policies. Therefore, first and foremost development we need to consider is the thorough integration of the different models into a solid methodological and deployable framework. Following, we need to consider the integration of other research methodologies related to data-driven modeling that can provide effective support to decision-making. Among these, the usage of Automated Machine Learning (AutoML) ([HKV19]) for selecting and fine-tuning data-driven models will serve both to optimize performance-based metrics and to consider ad-

ditional objectives and restrictions that are strongly related to actionable suggestions (e.g., robustness against adversarial attacks).

Thinking in terms of the single case studies presented within the CI support system, there are several improvements to be considered:

- **Combine clustering results with solver configurations.** Both the evolutionary solver and the clustering approach give us valuable insights into the integration of electric vehicles in public transportation and the existing behaviors in the driver population. Nevertheless, we have not put any effort onto combining the knowledge from both methodologies. It would be interesting, for example, to compare both techniques and look for significant links between certain driving profiles and fleet configurations. This combination will serve to better assess operational policies delivering a holistic view of the fleet.

- **Automated route planning.** Another intriguing expansion would be the ability to automatically generate optimal paths for a given mixed bus-fleet configuration, rather than using routes already established by the operator. This would be important in a demand-responsive transit scenario because ideal courses for conventional buses may not be optimal for electric vehicles due to differences such as lesser autonomy and sensitivity to road topology.

7.3 Research Trends and Challenges

In the next paragraphs, we present some research challenges and trends to improve performance and acceptability of incentive designs and actionable policy recommendations.

Explainability of actionable policies. A recent line of study focuses on the necessity of understanding how complex models analyze incoming data and generate decisions/actions from it. Recently, several methods have been described under the umbrella of the so-called *eXplainable Artificial Intelligence* (XAI) to explain the reasoning behind conventional black-box models, mainly created for prediction purposes. Nowadays, investigations on XAI are likely to focus primarily on the Deep Learning family of data-driven models. Intuitively, each action should be based on a sound knowledge of the underlying processes by which various components interact and impact the emerging phenomena. The interest of researchers in interpretable data-driven models is not new. Explainability and integrability are closely related in any application domain because, when it comes to system managers, ensuring that data-driven models can be understood by those who are not experts in AI can help them trust and favor their inclusion in the decision-making processes ([LSMVDS21]). A detailed understanding of the mechanics underlying the decisions made by a data-driven pipeline must support the prescription of policies based on the insights it suggests. Yet, explainability is one of the main barriers AI is facing nowadays in regard to its practical implementation. The inability to explain or to fully understand the reasons why state-of-the-art ML algorithms perform the way they do is a problem that find its roots in two different causes ([ADRDS$^+$20]): i) the delay for business sectors to adopt state-of-art models and methodologies proposed by the research community, and

ii) knowledge. In [LSMVDS21] authors define the requirements XAI needs to meet, as follows:

- To account for the consequences of actions and identify situations in which the decision-making based on the outputs of data-driven workflows may give rise to socially unfair scenarios due to the propagation of bias-related issues.
- To ensure the model performance is reliable and invariant under the same data stimuli, and potentially correct analysis of improper decision-making processes, thereby maximizing the trust and confidence in the output.
- To provide understanding about the prescriptive results of the data-driven model, shading light on the cause-effect relationship.
- To supervise the ethics of data-driven workflows by identifying potentially harmful uses of data according to the regulation framework, guaranteeing the privacy of personal data and certifying that the output of the model does not favor any kind of inequalities.

Undoubtedly, any effort to develop any decision-support system, or devise incentive designs and policies needs to consider the aforementioned *fairness*, *accountability*, *transparency*, and *ethics* concepts. Their unquestionable connection to actionability makes them the core of a promising future for data-driven modeling in dynamic and competitive systems, processes and applications.

Fairness Vs efficiency. Many multi-agent systems rely heavily on collaboration and teamwork. Teamwork has several benefits, but probably the most important is efficiency. At the same time, while agents — self-interested agents included — often agree that others gain from their effort, they also want the cost distribution among team members to be "fair," in the sense that expenses incurred are divided more or less equitably among team members. However, efficiency and fairness may constitute conflicting objectives.

As a social construct, fairness is inherently subjective [Lam02]. Its notion has been extensively studied within various fields such as political sciences and economics. This led to the emergence of a variety of fairness considerations including *impartiality*, *equity* and *equality*, *envy-freeness* allocation, among others. With the recent increased presence of Machine Learning (ML) in real-life decision-making situations, fairness has also been gaining importance in such field [MMS+21]. More recently, the notion of fairness has been brought to Multi-Agent Reinforcement Learning (MARL) systems. A line of work, for instance, focuses on applying equitable resource allocation [Lus12].

In competitive domains, [HLP+18] suggest to encode aversion for inequality in the agents reward. However, making agents learn this is not trivial. Indeed, if the reward is set to be a global system property, all agents will receive the same reward signal which is not efficient. This problem is sometimes referred to as the *credit-assignment problem*. Some work attempts to optimise the equality in the distribution of rewards of the agents in the most efficient manner possible [JL19]. This aspect is mostly crucial when it comes to devise incentive design to foster cooperation in MARL settings.

The literature approaches fairness as a goal individual agents' policies need to optimize. However, there seems to be a gap in the literature considering fairness and efficiency holistically. Indeed, in a real-world scenario, it may be that neither the efficient nor the equality goals are ideal, so it is imperative to study in-between solutions. The designer should be able to choose to sacrifice one of them, to a certain extent, for the other. There is not enough literature to support such decision. There is still no evidence of the outcome of mixing fair and efficient policies or even training these together in a MARL system. While the relationship between fairness and efficiency is popularly seen as a trade-off [PMF02], there is still a lack of evidence that is really the case in MARL settings. During the preparation of this dissertation we have performed an exploratory study in [SKPR22] addressing the distribution of rewards in MARL as a continuous spectrum of behaviors moving from fair to efficient policies. By relaxing the assumptions about the unique goal of fairness or efficiency the system seeks to promote, we aim to observe what solutions arise. We want to assess the impact of combining the fairness and efficiency goals in the testing and training phases. As one can reckon, this is perhaps the most long-term line of research pointed out in this thesis, even though it is closely related to the previous trend.

Appendix A

Marginal Research Efforts

This appendix describes the marginal research efforts developed along with the main thesis theme during the Ph.D. studies. A number of works have been produced spanning from the area of Intelligent Transportation Systems to the area of electricity and other types of markets. Further details for each project will be given in the next sections.

A.1 Research Efforts on Intelligent Transportation Systems & Artificial Transportation System

During the development of this dissertation we tried to provide a many-folds view of the ITS application domain. Having as main objective to analyze incentive and policy mechanisms from a MAS perspective, we started by analysing the requirements simulation frameworks should have to support successfully the development of future transportation systems. Following, we established approaches that allow us to instantiate artificial societies of transport users so as to understand the implication of their decisions on the system, and vice-versa, test the introduction of traffic artefacts by measuring the satisfaction of the end-users. Other side projects we performed int the area of the ITS include:

Taxi service analysis: Intermodal Interfaces and Dispatching Strategies Intermodal interfaces are extremely important for the transportation system as a whole and, therefore, the task of designing and scaling them is a crucial steps towards the improvement of passengers' experience. we discussed a methodology to properly design and assess taxi pickup hubs in airport terminals. Our approach is based on a multi-resolution analysis considering both macro and microscopic alignments. Furthermore, we analyze a number of dispatching strategies based on meta-heuristics to address the taxi-sharing problem. Results of these studies have been reported in:

- Passos, L. S., Kokkinogenis, Z., Rossetti, R. J., & Gabriel, J. (2013). *Multi-resolution simulation of taxi services on airport terminal's curbside.* In 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013) (pp. 2361-2366). [PKRG13]

- Silva, E., Kokkinogenis, Z., Câmara, Á., Ulisses, J., Urbano, J., Silva, D. C., & Rossetti, R. J. (2016). *An exploratory study of taxi sharing schemas.* In 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC) (pp. 247-252). [SKC+16]

Sensing approaches in ITS The study of human mobility as a whole is important when trying to comprehend traffic phenomena and design solutions to traffic-related issues. It is necessary to account for pedestrian and vehicles' mobility patterns to understand emerging interaction among them and the potential consequences to the surrounding transportation network. In a series of studies we considered and analyzed various techniques and methods of monitoring and detecting traffic events. In a first approach, we considered the limitations in the deployment of roadside units, we shaped our research on adopting monitoring technologies in urban contexts by considering bluetooth wireless communication as sensing devices for detecting traffic flow conditions. A second approach we considered was based on computer vision techniques where we reviewed the literature of such methods applied for the estimation of traffic flows. Additionally, we considered the adoption of a bird-view perspective using aerial drones to identify a statistical model of traffic dynamic in intersections. Finally, our last effort considered a new type of mobility study focusing on subjective user opinions of mobility networks. Taking advantage of the growth in popularity of opinion mining in social media, we presented an architecture of a system capable of automatically capturing user perspective towards a mobility network, based on web user-generated content. Results of these studies have been reported in:

- Filgueiras, J., Rossetti, R. J., Kokkinogenis, Z., Ferreira, M., Olaverri-Monreal, C., Paiva, M., & Gabriel, J. (2014). *Sensing Bluetooth mobility data: potentials and applications.* In Computer-based Modelling and Optimization in Transportation (pp. 419-431). Springer, Cham. [FRK+14]

- Kokkinogenis, Z., Filguieras, J., Carvalho, S., Sarmento, L., & Rossetti, R. J. (2015). *Mobility network evaluation in the user perspective: Real-time sensing of traffic information in twitter messages.* In Advances in artificial transportation systems and simulation (pp. 219-234). Academic Press. [KFC+15]

- Sandim, M., Rossetti, R. J., Moura, D. C., Kokkinogenis, Z., & Rúbio, T. R. (2016). *Using GPS-based AVL data to calculate and predict traffic network performance metrics: A systematic review.* In 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC) (pp. 1692-1699). [SRM+16]

- Lira, G., Kokkinogenis, Z., Rossetti, R. J., Moura, D. C., & Rúbio, T. (2016). *A computer-vision approach to traffic analysis over intersections.* In 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC) (pp. 47-53). [LKR+16]

Risk Analysis of Professional based on Drowsiness and Distraction Alerts Professional drivers are particularly exposed to drowsiness and distraction inasmuch as they drive for long periods of time and as a daily routine. In this context, we conducted two studies that aim to explore the data collected by a driver monitoring systems in order to analyze risk factors associated to the occurrence of driver distraction and drowsiness alerts and associated driving profiles. Results of these studies have been reported in:

- Ferreira, S., Kokkinogenis, Z., & Couto, A. (2019). *Using real-life alert-based data to analyse drowsiness and distraction of commercial drivers.* Transportation research part F: traffic psychology and behaviour, 60, 25-36. [FKC19]

- Soares, S., Kokkinogenis, Z., Ferreira, S., & Couto, A. (2020). *Profiles of Professional Drivers Based on Drowsiness and Distraction Alerts.* In International Conference on Human Interaction and Emerging Technologies (pp. 272-278). [SKFC20]

A Game-Theoretic formulation of Emerging Cooperation in Connected Mobility Cooperative Intelligent Transport Systems (C-ITS) are an important area of development for many domains. Road users and traffic managers share information and use it to coordinate their actions in order to improve road safety, traffic efficiency and comfort of driving, allowing the driver to make the right decisions and adapt to the traffic situation. In this project we performed a two-fold experimentation considering vehicular communications and studied how cooperation emerges. Firstly, we explored the strategy of conveying recommendations to drivers through buses that equipped with a variable message sign (VMS) on their rear and analysed the impact of such strategy on the system equilibrium. Secondly, we analyzed the effectiveness of the recommendation considering the decision-making process of individual drivers using a game theoretic framework in presence of imperfect communications. we reported the results of the studies in:

- Costa, A., Rossetti, R. J., & Kokkinogenis, Z. (2020). *Improving Route Choice: Communication Issues in Moving Variable Message Signs.* In 2020 IEEE International Smart Cities Conference (ISC2) (pp. 1-8). [CRK20]

- da Costa, A. R., Kokkinogenis, Z., d'Orey, P. M., & Rossetti, R. J. (2022). *Assessing Communication Strategies in C-ITS Using n-Person Prisoner's Dilemma.* In EPIA Conference on Artificial Intelligence (pp. 322-335). [dCKdR22]

Assessing Vehicular Fog Computing In a vehicular fog computing paradigm, connected autonomous vehicles are envisioned as processing nodes (i.e. fog nodes) so that end-devices may offload processing tasks to them. As such, both local and distributed processing on fog nodes will depend heavily on wireless network conditions and the current traffic demand. In two distinct studies we analyzed both the effect of the application heterogeneity and wireless network conditions. In the first study we focuse on how heterogeneity affects the ability of IoV and VFC to meet application requirements. We argued that vehicles need to follow request-processing-response-actuation programming model based on distributed auction protocol to match clients and servers and still meet latency requirements. In the second study, we investigated the trade-offs on the operation of fog nodes under different vehicle densities and network conditions and formalize a Time Constrained One-Shot Open First Price Auction for resource allocation in vehicular fog computing. Results of these studies are reported in:

- de Mendonça Junior, F. F., Lopes Dias, K., d'Orey, P. M., & Kokkinogenis, Z. (2021). *FogWise: On the limits of the coexistence of heterogeneous applications on Fog computing and Internet of Vehicles.* Transactions on Emerging Telecommunications Technologies, 32(1). [dMJLDdK21]

- de Mendonça Junior, F. F., Kokkinogenis, Z., Dias, K. L., d'Orey, P. M., & Rossetti, R. J. (2022). *The trade-offs between Fog Processing and Communications in latency-sensitive Vehicular Fog Computing.* Pervasive and Mobile Computing, 84. [dMJKD+22]

A.2 Research Efforts on Markets

In Chapter 3 we discussed the importance of markets as coordination enablers. We extended our research effort in analyzing market structure by a) studying carbon markets in their quest to fight against climate change by reducing greenhouse gases (GHG) emissions, and b) assessing the introduction of blockchain technology in its task of controlling and guaranteeing transactions in a distributed fashion. With respect to carbon markets, we considered an agent-based social simulation model that can experiment with different regulatory mechanisms of carbon emissions. With respect to blockchain technology, we addressed the place of smart contracts within a traditional blockchain and agreement pipeline. We have argued that such a contract should be an integral part of the agreement and not incorporating agreement aspects. After reviewing an agreement pipeline from a smart contract perspective, we proposed a hybrid approach combining MAS and smart contracts that can allow for placing regulation mechanisms and discussed how a blockchain REST API can help to experiment with this kind of networks. Results of these studies are reported in:

1. Rúbio, T. R., Kokkinogenis, Z., Cardoso, H. L., Rossetti, R. J., & Oliveira, E. (2019). *Regulating blockchain smart contracts with agent-based markets.* In EPIA Conference on Artificial Intelligence (pp. 399-411). [RKC+19]

2. Narciso de Sousa, J. B., Kokkinogenis, Z., & Rossetti, R. J. (2021). *Carbon Market Multi-agent Simulation Model.* In EPIA Conference on Artificial Intelligence (pp. 661-672). [NdSKR21]

A.3 Research Efforts on Multi-Agent System based Platform for the Development of Autonomous Aerial Drones

Aerial Drones have acquired prominence in the last decade as a result of their successful military endeavors. Since then, various civil applications have emerged with the goal of using this technology to replace human operators in dangerous circumstances. Indeed, current research approaches in drone development strive to integrate three intriguing features: a higher level decision-making process, autonomy in performing actions, and coordination of efforts toward a shared objective in the event of multi-unit applications. Our research is twofold. First, we focused on developing adequate simulation tools for aerial drones operations. In general we necessitate the use of such computational tools to avoid damage to expensive equipment and the wasting of resources that might be used to advance the development life cycle. Upon various considerations about which paradigm can fulfil the requirements for a collaborative aerial drone simulation tool for real-scenario indoor and

outdoor applications, we ended up adopting the *symbiotic simulation* approach. In a second direction, we presented the conceptualization and development of a platform to design, implement, multiple instances of autonomous aerial drones. In this context autonomy is intended not only as making decisions but mainly as cognitive process. The envisaged architecture is a hybrid approach; low level decisions (actions) are executed in a reactive fashion, while processes such as can be the one of planning follow a deliberative reasoning. The capabilities of the platform were extended the symbiotic simulation tool. Therefore we created a synergy between virtual models of agent-based entities and real autonomous aerial drones, where one can explore various what-if scenarios for the definition of the application aspect one intends to explore. Results of these research efforts are reported in:

1. Veloso, R., Oliveira, G., Passos, L. S., Kokkinogenis, Z., Rossetti, R. J., & Gabriel, J. (2014). *A symbiotic simulation platform for agent-based quadcopters.* Proceedings of the 9th Iberian Conference on Information Systems and Technologies (CISTI 2014). [VOP+14].

2. Veloso, R., Kokkinogenis, Z., Passos, L. S., Oliveira, G., Rossetti, R. J., & Gabriel, J. (2014). *A Platform for the Design, Simulation and Development of Quadcopter Multi-Agent Systems.* Proceedings of the 9th Iberian Conference on Information Systems and Technologies (CISTI 2014). [VKP+14].

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