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Modeling the Impact of Emission Credit Systems on Automotive Product Portfolios: A Mathematical Analysis of Policy Effects in Europe, China, and the U.S. Under Different Demand Scenarios

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Abstract

In the midst of the global climate crisis, governments worldwide have implemented a range of emission policies aimed at encouraging more production of the environmentally friendly vehicle. However, the exact impact of these policies on automakers' production portfolios and profitability remains uncertain and challenging to anticipate. This paper presents a comprehensive analysis of three major emission regulation policies enacted by the European Union (EU), China, and the United States (U.S.), evaluating their influence on car manufacturers. Leveraging a mathematical model, this paper adopt the perspective of individual manufacturers seeking to maximize revenue, delving into the intricacies of these policies. Furthermore, this article conduct sensitivity and factorial analyses to assess the impact of policy parameters. The findings reveal that all three major emission policies contribute to an increase in the production of low-emission vehicles. However, China's policy has the least impact on manufacturers' profits and relies more on market demand to reduce the average carbon fleet emissions compared to the policies in the EU and the U.S. In conclusion, this paper underscores that different policy systems yield varying profit outcomes for manufacturers, necessitating adjustments to production portfolios for sustained profitability and the significance of mathematical models in aiding manufacturers' understanding of evolving policies and making informed predictions in a dynamic regulatory landscape.

Keywords: automotive production; green transition; international emission policies; regulatory impact; sustainability

1. Introduction

As modern industrialization surges forward, humanity confronts the complex challenges of climate change. This encompasses the onset of extreme weather patterns and elevated temperatures, both driven by the incessant release of copious amounts of greenhouse gases into the atmosphere. The excessive emissions of greenhouse gases, such as carbon dioxide (CO_2) and methane (CH_4), instigate the greenhouse effect, culminating in the far-reaching issue of global warming. This phenomenon poses a threat to the existing ecosystem, manifesting in disruptive weather patterns and extreme climatic events (Yoro & Al., 2020). Notably, the primary source of CO_2 emissions stems not only from industrial production but also from vehicular exhaust (Huang et al., 2015). Traditional vehicles predominantly powered by gasoline and diesel generate substantial CO_2 emissions in day-to-day usage. In response to this environmental challenge, the electric vehicle concept emerges as a viable solution. By utilizing electricity as the primary power source, electric vehicles could reduce carbon emissions, positioning them as a more eco-friendly alternative (Costa et al., 2021)

Currently, there are four main types of vehicles: Internal Combustion Engine Vehicles (ICEV), Plug-in Hybrid Vehicles (PHEV), Battery Electric Vehicles (BEV), and Fuel Cell Elec-

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tric Vehicles (ICEV) (Vacheva & Hinov, 2019). ICEV cars are the most traditional, powered by gasoline and emitting a relatively high amount of CO2. BEV and FCEV are pure electric vehicles with zero carbon emissions, collectively referred to as ZEV (Zero Emission Vehicles). The distinction between these two vehicle types lies in their power sources: BEVs use batteries charged with electricity, while FCEVs utilize biofuels and hydrogen-powered fuel cells, which can also be considered hydrogen-powered vehicles (Parikh et al., 2023). PHEVs represent a middle ground, with lower carbon emissions compared to ICEVs. They operate on a hybrid power source, utilizing both electricity and petrol or gasoline simultaneously. These different vehicle types have significant variations in production costs and sales revenue, depending on factors such as production year, type, and size (Lipman & Delucchi, 2006).

The ZEV and PHEV vehicle types produce less CO2 with lower tailpipe emissions, which can help mitigate the problem of global warming. However, despite the increasing popularity of electric and low-carbon emission vehicles, the cost of new energy vehicles remains higher than traditional vehicles, leading to lower profits for manufacturers (Cuenca et al., 2000). Vehicle producers need to maintain market competitiveness and prioritize profit and financial gains, making it challenging to persuade them to prioritize the production of less profitable but environmentally friendly vehicles. To encourage manufacturers to reduce fleet emissions, which represent the average amount of CO2 produced across their production portfolio, various governments have introduced policies and regulations. Different governments have adopted unique approaches to establish country-specific policies (An et al., 2011). However, the precise effectiveness of these policy systems on manufacturers' production portfolios remains unclear.

This article focuses on three primary markets: Europe, China, and the USA, each with its own emission regulations. In Europe, the emission policy is referred to as the Super Credit Policy, in China, it is known as the Dual Credit Policy, and in the USA, it is named the US Credit Policy. Further details about these regulations can be found in Section 3.4.

In this scenario, two stakeholders exist: the manufacturer and the policymaker. For the manufacturer, they need to determine quickly how different policies will affect their business profit and make quick responses to the production portfolio to ensure profitability. For the policymaker, they need to balance the profit of the manufacturer and the carbon emission. As Dominioni and Faure (2022) shows, an imbalanced policy can lead to either a loss of tax income or the limited effectiveness of emission policies. Although the government has spent a lot of time discussing the details of the policy and understands that even small parameter changes can affect policy effectiveness, evaluating the policy's effect is complex. Policies must precede market reactions, and past results are unreliable predictors due to changing demand and production situations. Once a policy is published, it is difficult to withdraw. For manufacturers, regardless of how the policy performs, they need to understand how different policies and changes in policy parameters will affect their production portfolio and revenue to adjust their business strategy. Different countries have their own goals in setting up policies, and it is essential for manufacturers to analyze how different policies in different countries differ to differentiate their production strategy and ensure better profitability.

Overall, this study aims to compare various emission policies and assess their impact on manufacturing portfolios for producers across different parameter scenarios in a quantitative manner. In this article, operations research methods are used to simulate the effect of different policies based on realistic test instances. By constructing mixed-integer linear optimization models for different policies and demand scenarios, policymakers as well as vehicle manufacturers can have a detailed quantitative view to assess policy effectiveness (Thies et al., 2022). The data comes from large global vehicle manufacturer, and the policy information is based on the current policy setup as of 2023. Moreover, since the mathematical model is flexible in changing parameters, the parameters and data can be adjusted to reflect the current situation and make more accurate predictions and analyses.

The remainder of this study is structured as follows: In Section 2, I discuss the literature related to this topic on finding out the emission policy impact. In Section 3, I present the model with detailed formulation and parameters, along with different models of the three emission policy systems in Europe, China, and the US. In Section 4, I show how the model is solved for different policy systems, with the main discussion focusing on the Super Credit System in Europe. In Section 5, I list out the test instances performed and the structure of the design of the experiment in evaluating different policy systems. In Sections 6, I present the final results, including the detailed portfolio, as well as sensitivity and factor analysis for different demand scenarios and parameter settings. Finally, in Section 7, I draw conclusions regarding the different policy systems and provide an outlook for further research.

2. Literature Review

Various approaches have been proposed to assess the effects of emission policies on car manufacturers, and they can be classified into five primary categories. Empirical studies and economic models rely on historical data and economic principles to conduct analyses on a broad scale. Market scenario models create hypothetical market conditions to evaluate policy impacts. A technology strategy model employs mathematical modeling to assist manufacturers in making decisions regarding the adoption of different vehicle models with various motive technologies. Simulation-based planning models use simulations to project long-term effects of the policy regulation for the manufacturer. Individual vehicle manufacturer mathematical models are tailored to specific manufacturers for in-depth analysis with output of detailed production plan and fleet emission trend.

In the category empirical studies and economic models, with the empirical studies gather data on emissions, production, and market behavior to analyze the impact of emission policies and the economic model use economic principles to predict how policy changes may affect car manufacturers, such as changes in costs, prices, and market demand. For the empirical studies Bergek and Berggren (2014) reviewed the empirical studies on environmental policy and found that policy instruments play a crucial role in driving environmental innovation across sectors. Also, (Y. Wang et al., 2018) analyzed compliance strategies of four different automakers under dual-credit regulations, considering fuel economy and NEV (New Energy Vehicle) production which includes the ZEVs (Zero Emission Vehicles) and PHEVs (Plug-in Hybrid Electric Vehicle), comparing their approaches and suggesting cost-effective strategies with regulatory improvements.

Besides these empirical analyses, the economic model and pricing model have been built up to analyze how the policy would affect the vehicle manufacturer in a broad vision. (Moran et al., 2020) conducted micro-level studies with a multi regional input-output economic model to analyze the consumer-oriented policy and showed that these policies would reduce carbon emissions by about 25%. Additionally, the government pricing model of dual-credit policy published by (Yang et al., 2023), which compared with the market pricing model, shows that the dual-credit policy benefits energy saving and emission reduction in the transport sector. Moreover, in the study by (Ma et al., 2021), a supply chain model includes two stakeholders, the engine supplier and automakers, to analyze the carbon emission policy effect on the production of the ICEV and NEV vehicle. (Michalek et al., 2005) also considered the impact of the competition of other manufacturer in the paper and proposed mathematical models of engineering performance, consumer demand, and manufacturing costs, combined with game theory for the market segment. For these models, the trend could be observed from the economic perspective, but it could be too broad in scope that makes lack of some precision in explaining some details in the impact of the emission policy on the production plans of the individual manufacturer.

Besides the economic models, various market scenario models have been used to analysis the impact of the emission policy on the manufacturer's portfolio. These models creating various hypothetical market scenarios including the transportation sector and then evaluating how different emission policies would impact car manufacturers under these scenarios. For example, Thiel et al. (2016) used a TIMES-based energy system model to examines the impact of stricter EU CO2 car legislation on transport-related emissions, Electric vehicle uptake, oil consumption, and energy costs. This model is a modeling platform that consider factors like energy production, costs, and environmental impact and could helps make informed decisions about emission policies and resources. Hill et al. (2018) provided three models of PRIMES (global energy-economic model)-TREMOVE (transportation policy), GEM-E3T (model with macroeconomic, energy, and environmental policies) and the JRC DIONE (model for assessing energy and environmental policies) to analysis the overall market situation in considering energy, climate, transportation and the Europe emission policy. These models all reach similar conclusion that the EU policy are effective in reducing GHG(Greenhouse Gas) emissions. The ALTER-MOTIVE modelling method also been conducted by Ajanovic and Haas (2017) to integrate the energy system and transportation showing that GHG emissions could be reduced at least by 33% in a selected policy scenario. Other than these pre-formed model, Ou et al. (2018) develops the New Energy and Oil Consumption Credits Model to quantify the impacts of this policy in scenario from 2016 to 2020 to discuss the effect of the dual credit system in China on the electric vehicle sales. While these scenario models are useful for generating convincing results, they may oversimplify market conditions and the behaviors of individual manufacturers. These models can assess the effects of emission policies on a broad scale and from a market perspective, but they may not provide a comprehensive understanding of how individual car manufacturers would be impacted by or respond to these policies.

Speak to make analysis from individual level, there are some studies modeled the problem of individual car manufacturers to find profit maximizing technology strategies considering emission policies. S. Wang et al. (2018) build a mixed-integer mathematical model with decision variables representing various motor technologies in a technology combination (TC) problem. This model is designed to describe an automaker's decision-making process, and I utilize a genetic algorithm to assess the impact of China's dual credit policy from 2020 to 2025. Moreover, Romejko and Nakano (2017) increase the range of the motor technology path for the vehicle projects and explores a more diverse range of eight alternative fuel vehicles (AFVs), including EVs, FCVs, CNG (Compressed Natural Gas) vehicles, and more, to predict an optimal AFV portfolio for achieving economic and energy security goals. Moreover Zhu et al. (2022) proposed a decision-making algorithm for automakers' production strategies under the dual-credit policy in China. This algorithm reveals how automakers' choices transition between strategies based on thresholds and government targets. Furthermore, other than changing between the constraints and parameter, Kellner et al. (2021) also use multi-objective optimization method analysis in the technology selection to find the optimal power train technology portfolio. For these models, some individual level of the vehicle portfolio planning has been performed. However, these models only provide the outcome of which motor technology to initialize, without offering information on the actual quantity produced for different vehicle technology types. Consequently, they do not offer a comprehensive view of the resulting average fleet emission values or the detailed cost structure of vehicle manufacturers and are not capable for providing a very clear picture of the vehicle portfolio and the impact of emission policy on these portfolios.

Simulation method is also a popular modeling method to obtain vehicle portfolios. Kieckhäfer et al. (2012) at year 1970 used a hybrid market simulation approach for strategic planning of automotive vehicle portfolios to predict powertrain market shares across vehicle sizes based on portfolio offerings, consumer behavior, and market conditions. Also Kieckhäfer et al. (2009) creates a framework using system dynamics and agent-based simulation to analyze the product strategies which aid manufacturers in effective technology introductions across vehicle classes while considering regulations and markets. Moreover the NW (Newman and Watts) 'small world' network model also been used by Hu et al. (2020) to explore the dynamic effects of different policies on the diffusion of electric vehicles. For these simulation model, they could provide a close to reality output for the vehicle portfolio result thus indicate the impacts of the emission policy, but the model would take long times to be solved. It could be inefficient in time when implementing large number of testing scenarios into those simulation model for getting the solution insights.

Recently, Thies et al. (2022) proposed a novel model that concentrates on the individual vehicle manufacturing portfolio. This article analysis how the EU emission policy effects the vehicle portfolio using optimization model from the perspective of an individual vehicle manufacturer. This model has provided a detailed production portfolio, showing the optimal quantity of each vehicle type to be produced annually, along with a comprehensive resource plan and accurate average fleet emissions for each year's production and provide a basic framework of the optimization model used in this article. In this article, the base model of Thies et al. (2022) is extended by considering not only the EU policy but also the other two major policy system in China and the US. Furthermore, the EU policy is considered in more detail, as the super credit relaxation is considered. This novel model offers a more comprehensive and realistic analysis of policy effects from the perspective of individual car manufacturers and can be solved in few minutes. This model provides detailed information, including the vehicle initialization plan, production quantity for each vehicle type in each year, average fleet emissions in each year, market share of vehicle types, and the detailed cost structure. Moreover, it allows for easy parameter adjustments to customize the results as the policy changes.

3. Method

This section presents a mathematical model for project portfolio planning considering different emission policies. The overall road map for the model formulation is presented in Section 3.1 and Section 3.2 explains all the parameter information for the mathematical model. After that, a base model without emission policies is presented in Section 3.3, before it is extended by the emission policies for Europe, China and the U.S. in Section 3.4.

3.1. Model Road Map

Figure 1 describes the roadmap for the optimization model in this article. The planning horizon is 10 years, from 2025 to 2035, during which the manufacturer can change its portfolio production decisions. For the period outside the planning period, the settings remain fixed.

Within the planning horizon, the manufacturer can make several decisions, with the primary one being the determination of production quantities (q_{vt}) for each vehicle (v) in each period (t). To ensure these production quantities, the resource plan has also been established, which includes the capacity (k_{rt}) for each resource (r) in each period (t). Additionally, the resource adjustment plan contains (k_{rt}^{Rampup}) and ($k_{rt}^{Rampdown}$), representing the required increase and decrease amounts for resource (r) in period (t). The objective function aims to maximize the Net Present Value (NPV) for the entire production portfolio, which is discounted the manufacturer's profit obtained by subtracting all costs from the revenues. Revenues encompass sales revenue generated from vehicle sales throughout the planning period, as well as end-of-period capacity cash-out income. Costs include production expenses, which consist of both fixed and variable costs related to vehicle production, expenses for increasing or decreasing resources to maintain production capacity, development costs for initializing new vehicle projects, and penalty costs or gains dependent on the specific policy system in place.

Several constraints bind the decision-making process for vehicle production and can be categorized into five main categories. The vehicle project constraints help determine the initialization of different vehicle projects each year and limit the maximum number of projects that can be started. The production resource constraints are used to ensure sufficient resources are available for production. The vehicle demand constraint is employed to prevent the sale of more vehicles than the market demand, and the production volume constraint is used to ensure the minimum production volume each year. The policy-related constraints in different policy systems impose penalties or restrictions on the average fleet emissions of the production portfolio.

The inputs for modeling the production process constraints are depicted in Figure 1. The vehicle projects include several pre-defined projects categorized by powertrain technology type, size, production year, and power range class. Some vehicle projects are already determined before the planning horizon. Each vehicle project has its own production cost, sales revenue, and tailpipe line emission value. Development costs are assumed to be the same for all vehicle projects, and the maximum life cycle is equal for all projects. After 2025, within the planning period, the manufacturer can initialize new vehicle projects if suitable.Each vehicle project requires production resources. Before the planning period, the current on-hand resources are pre-defined. The manufacturer must ensure that resources can meet the production quantity of vehicle projects, which includes decisions on ramping up or down capacity. Resource costs include fixed and variable costs, with the fixed cost per production resource potentially decreasing due to economies of scale. Sales quantities must not exceed the market demand for a given year, segmented by vehicle type, size, and power range

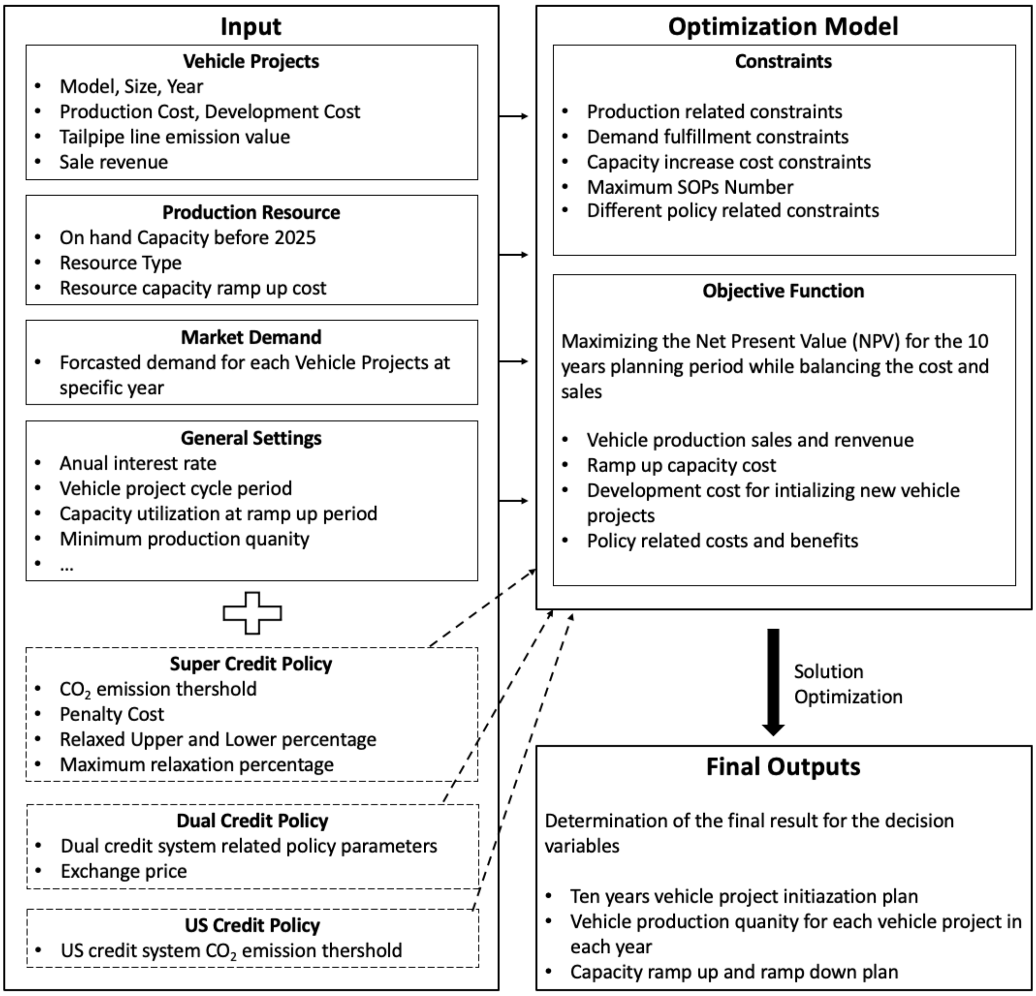


Figure 1: Optimization Model Road Map

(e.g., $ICEV\_medium\_low$). Multiple vehicle projects can be considered for several years within a market demand segment, but each vehicle project is associated with only one market segment. Quantities below market demand are assumed to be sold, and any unfilled demand is considered to be lost with no capacity payback. The general settings define the framework for general parameters, such as the assumed annual interest rate for NPV calculation, utilization loss due to capacity increment, and the minimum production quantity required to stay on the market, with full details described in section 3.2.3.

In addition to the basic setup, one of the policies from Super Credit Policy in Europe, Dual Credit Policy in China, US Emission Policy in the United States, or no Policy should be chosen to form the final policy-specific optimization model. Each policy entails specific parameters and formulas to be considered. The parameter values for different policies are based on current research in 2023, combined with personal assumptions, and all are related to the CO_2 average fleet emissions, as described in section 3.4.

Once these setups are incorporated into the model and the model is solved, the final objective value becomes available, along with detailed values for revenues and various cost sectors. Additionally, the fleet emissions for each vehicle project (v) in each period (t) can be determined by multiplying the carbon cycle emissions (E_v) by the quantity produced (q_{vt}) each year.

All details about the formulation of the optimization model are presented in section 3.3.

3.2. Parameter Information for the Vehicle Project Portfolio Planning

This section provides detailed parameter information, including sets, indices, decision variables, and descriptions for all parameters used in the model.

3.2.1. Sets & Indices

The model uses several sets and indices, which are described in Table 1. These sets and indices are essential for defining the parameters and decision variables in the model.

3.2.2. Decision Variables

There are 11 sets of decision variables described in Table 2. Three of these variables are binary variables, while

Table 1: Sets and Indices

Set & Indices		
Set	Index	Description
V	v	Vehicle projects
$X \in V$		Vehicle project start before the planning horizon
T	t	Periods
$P \in T$		Periods in planning horizon
M	m	Market segments
R	r	Production Resources
$E \in R$		Existing production resources at the beginning of the planning horizon

the rest are continuous variables. These decision variables play a critical role in the model, enabling the optimization of the vehicle portfolio and the assessment of various policy impacts.

3.2.3. Parameters

Table 3 concludes all the parameters used for the mathematical model, including the basic model as well as the additional emission policy model and separated by categories. The parameter contains type constant, variable, and vector.

3.3. Mathematical Formulation for the Base Model

This section describes the model for the base model without the emission policy but provides an explanation of the objective function and the constraints in the context of a pure vehicle manufacturer setting.

3.3.1. Objective Function

For the objective function, the goal is to maximize the net present value (NPV) of the vehicle project in ten years period. The interest rate is assume to be 5%, and the monetary value is calculated in each year and return the final NPV value base on year 2025. The objective function consists of three major parts which are the net profit of the production portfolio, the development cost and capacity increment cost, and finally the capacity cash back cost calculated and the end of the production planning phase at year 2035.

For the net profit of each year in the planning period, it adds up all sale revenue according to the production quantity and minus the production variable cost as well as the fixed cost, also the penalty cost due to the emission policy would be deducted according to different policy types.

For the development cost and capacity increment cost although the cost are spent on specific year in the production planning period, but it is assumed that the payment does not due immediately. The payment and deduction could be evenly distributed in 7 years period with each year about 14.3% of the total cost paid. $Vect_{vt}^{RD}$ is the parameter used for calculate the distribution of the cost and could also be counted after the production period. So the net NPV is summation for a all periods which is $t \in T$, from 2025 to 2050.

For the third part of the capacity back value, it is calculated at the end of the planning period at year 2035. This term used to count back the capacity value to prevent the model over estimated the cost for the last few years capacity increase. For the capacity back cost, it is assumed that the resource on hand would retain it's value in 10 years period and for each year, the value would depreciate by 10%. For example, for the resource in 2030, the resource would be capacity back with the rest value of 50%.

Objective Function:

Maximize NPV with:

$$\begin{aligned} \max \mathrm{NPV} = & \\ & \sum_{t\in P}((TC_t^{SaleProd} - TC_t^{ProdFixed} - TC_t^{Penalty}) \cdot dr_t) \\ & -\sum_{t\in T}((TC_t^{RD} + TC_t^{Capacity}) \cdot dr_t) + TR^{CapaBack} \cdot dr_{T^{max}} \end{aligned} \tag{1}$$

with

$$TC_t^{SaleProd} = \sum_{v\in V}((s_v^{unit} - c_v^{Unitvar}) \cdot q_{vt}) \tag{2}$$

$$TC_t^{ProdFixed} = \sum_{r\in R}(c^{Resource} \cdot k_{rt}) \tag{3}$$

$$TC_t^{Penalty} = c_t^{Penalty} \tag{4}$$

$$TC_t^{RD} = \sum_{v\in V}(c_v^{RD} \cdot Vect_{vt}^{RD} \cdot y_v) \tag{5}$$

$$\begin{aligned} TC_t^{Capacity} = & \sum_{r\in R}\sum_{t\in P}(c^{RampUpFixed} \cdot Vect_{\tau t}^{PC} \cdot y_{rt}^{RampupBin} \\ & + c^{RampUpVar} \cdot Vect_{\tau t}^{PC} \cdot k_{rt}^{Rampup}) \end{aligned} \tag{6}$$

$$TR^{CapaBack} = \sum_{r\in R} z_r^{RestValue} \tag{7}$$

3.3.2. Constraints

From the baseline model, there are four categories of constraint sets listed below. The constraints for different emission policies are in Section 3.4.

For the vehicle projects constraints set, it consists of constraints related to vehicle project initialization. Constraint (8) sets up the initial start for the vehicle project before 2025, the planning horizon. Constraint (9) uses a big number M to switch the binary variable for the start of the new vehicle project. Constraint (10) limits the allowed start for the number of vehicle projects in every year due to resource limits, and Constraint (11) forces the quantity produced to 0 if the vehicle exceeds the project life cycle of $t^{\max}$ years.

Table 2: Description of Decision Variables

Decision Variables			
Variable	Type	Range	Description
y_v	Binary	$\{0,1\}$	Vehicle project starting indicator with 1 meaning vehicle v is realized and 0 otherwise
q_{vt}	Continuous	$\mathbb{R}^+$	Number of vehicle project v produced at time period τ
k_{rt}	Continuous	$\mathbb{R}^+$	Capacity of resource r in period t
k_{rt}^{Rampup}	Continuous	$\mathbb{R}^+$	Increase of production resources r at the beginning of period t
$k_{rt}^{Rampdown}$	Continuous	$\mathbb{R}^+$	Decrease of production resources r at the beginning of period t
y_{rt}^{Rampup}	Binary	$\{0,1\}$	Resource increase indicator with 1 meaning there is an increase in resource r at the beginning of period t, with 0 otherwise
$z_r^{RestValue}$	Continuous	$\mathbb{R}^+$	Residence Value for resource r at the end of the planning horizon
$c_t^{Penalty}$	Continuous	$\mathbb{R}^+$	Penalty cost paid for the excess CO_2 Emission in period t
P_t^{relax}	Continuous	$\mathbb{R}^+$	Super credit policy relaxed percentage
y_1	Binary	$\{0,1\}$	Binary variable used to form maximum or minimum constraint
D_t^{Dual}	Continuous	$\mathbb{R}^+$	Cost paid(+) or Revenue earned (-) for dual credit policy

For the production resource constraints, Constraint (12) describes the resource usage constraint, and Constraint (13) indicates that in the ramp-up period, the resource would only be available at $\theta^{\max}$ percentage. Constraint (14) adjusts the on-hand resource at each year of the planning period after the previous ramp-up and ramp-down decisions that would be made. Constraint (15) switches on the fixed cost for ramping up the capacity. Constraint (16) calculates the rest value of the on-hand resources at the end of the planning year 2035, with V^{res} representing the remaining value, estimated as 5% of the total cost paid for increasing this amount of resource.

Constraint (17) is the vehicle demand constraint to ensure that the production volume, which is less than the demand, would be sold to earn profit. Constraint (18) guarantees the minimum production volume in each year in the planning period.

Vehicle Projects

$$y_v = y_v^{initial} \qquad \forall v \in X \quad (8)$$

$$q_{vt} \leq M \cdot y_v \qquad \forall v \in X, \forall t \in P \quad (9)$$

$$\sum_{v \in V: SOP_v = t} y_v \leq SOP^{\max} \qquad \forall t \in P \quad (10)$$

$$q_{vt} = 0 \qquad \forall v \in V, \forall t \in T : t \leq SOP_v \vee t \geq SOP_v + t^{max} \quad (11)$$

Production resources

$$\sum_{v \in V: r_v = R} q_{vt} \leq k_{rt} \qquad \forall r \in R, \forall t \in P \quad (12)$$

$$\sum_{v \in V: r_v = R} q_{vt} \leq \theta^{max} \cdot k_{rt} \qquad \forall r \in R, \forall t \in P : t = t_r^{Rampup} \quad (13)$$

$$k_{rt} = k_r^{initial} + \sum_{\tau \in P: \tau \leq t} (k_{r\tau}^{Rampup} - k_{r\tau}^{Rampdown}) \qquad \forall r \in R, \forall t \in P \quad (14)$$

$$k_{rt}^{Rampup} \leq M \cdot y_{rt}^{Rampup} \qquad \forall r \in R, \forall t \in P \quad (15)$$

$$z_r^{RestValue} \leq V^{res} \cdot \sum_{t \in U} ((y_{rt}^{Rampup} \cdot c^{RampUpFixed}) + (c^{RampUpVar} \cdot k_{rt}^{RampUp})) \qquad \forall r \in R \quad (16)$$

Vehicle Demand

$$\sum_{v \in V: m_v = m} q_{vt} \leq d_{mt} \qquad \forall m \in M, \forall t \in P \quad (17)$$

Production volume

$$\sum_{v \in V} q_{vt} \geq q^{\min} \qquad \forall t \in P \quad (18)$$

Table 3: Detailed Parameter Information

Parameter			
Parameter Category	Parameter	Type	Description
Vehicle Projects	SOP_v	Vector	Start of production time for vehicle project v
	$c_v^{Unitvar}$	Constant	Unit variable cost for vehicle project v
	s_v^{Unit}	Constant	Unit sale revenue for vehicle project v
	E_v	Vector	CO_2 cycle emission of vehicle project v
	m_v	Vector	Market segment type of vehicle project v
	r_v	Vector	Resource type needed for vehicle project v
	t^{max}	Constant	Maximum duration of the selling time period
	$Vect_{vt}^{RD}$	Vector	Distribution of cash flow: Percentage of total development cost for vehicle project v in period t
	c_v^{RD}	Constant	Development cost for a new vehicle model
	$y_v^{initial}$	Vector	Preset vehicle realization indicator for vehicle project v
Production Resource	$c^{RampUpFixed}$	Constant	Fixed cost for ramping up production resources
	$c^{RampUpVar}$	Constant	Unit variable cost for the production resources
	t_r^{Rampup}	Vector	Ramp-up period for production resource r
	$Vect_{t_{cur}t_{rampup}}^{PC}$	Vector	Distribution of cash flow: Percentage of total production cost for ramp-up period t_{cur} distributed in current period t_{rampup}
	$c^{Resource}$	Constant	Constant cost for each unit of production resource on hand
	$k_r^{initial}$	Vector	Capacity of production resource r before the planning horizon
	V^{res}	Constant	Residence value for production resource at the end of planning horizon
Demand	d_{mt}	Vector	Number of vehicles demanded in market segment m at period t
	P_{min}	Constant	Minimum percentage of total demand needed to be fulfilled
Emission Regulation	E_t^{Law}	Constant	Total CO_2 fleet emission threshold in period t
	σ_{low}	Constant	The maximum fleet emission value for the category of low emission vehicles in the super credit policy system
	$\gamma_{mutiplier}$	Constant	PHEV multiplier factor in super credit policy system
	$E_t^{RelaxLaw}$	Variable	Relaxed threshold for total CO_2 fleet emission in period t
	$P_t^{EVthres}$	Variable	The regulated electric vehicle percentage to meet the relaxation criteria in period t
	$P^{SuperMax}$	Constant	Maximum allowance for relaxation in Super Credit System
	c^{CO_2}	Constant	Unit penalty payment cost per g/km for each vehicle sold
	S_t^{CAFC}	Variable	Total standard CAFC credit provided in period t
	A_t^{CAFC}	Variable	Actual CAFC credit consumed in period t
	S_{vt}^{FC}	Variable	Fuel consumption standard for vehicle project v in period t
	A_{vt}^{FC}	Variable	Actual fuel consumption for vehicle project v in period t
	W_v^{FC}	Variable	Weight factor for low emission vehicle project v in CAFC credit
	S_t^{NEV}	Variable	Total standard NEV credit for new energy vehicles required in period t
	A_t^{NEV}	Variable	Actual NEV credit gained for new energy vehicles in period t
	k_v	Variable	Weighted NEV credit ratio factor for vehicle project v
	R_t	Variable	Target ratio in period t discounted for NEV credit
	C^{Dual}	Constant	Monetary value for one dual credit in dual policy system

Table 3 — continued

Parameter			
Parameter Category	Parameter	Type	Description
Other Parameters	i	Constant	Assumed interest rate
	dr_t	Vector	Discount rate at period t
	q^{min}	Constant	Minimum production number required in each period
	$\theta^{\max}$	Constant	Maximum utilization of production resources in the ramp-up period
	SOP^{max}	Constant	Maximum number of vehicle project initializations in each period
Others	M	Constant	Large number used for modeling
	T^{max}	Constant	Last period in the planning horizon T

3.4. Mathematical formulation for Different Policy Systems

This section explains the three major emission policy models: the Super Credit System in Europe, the Dual Credit Policy in China, and the Emission Policy in the US.

3.4.1. Super Credit System in Europe

For the Super Credit System, the EU government has set a target tailpipe emission threshold to measure the average carbon emission each year. Furthermore, in Europe, there are not only simple penalty regulations for carbon emissions for vehicle manufacturers. Beginning in 2025, the EU Commission announced a Super Credit System on top of the CO_2 emission regulations. In simple terms, car producers can gain more CO_2 threshold reductions when they produce more low carbon emission vehicles. The definition of low carbon emission is when the CO_2 emissions of the car are lower than 50 g/km. With this Super Credit System, vehicle manufacturers would be more incentive to produce low or non-carbon emission vehicles since they would gain more CO_2 emission allowances or incur fewer penalty costs from a larger production of low carbon emission vehicles.

In the Super Credit System in Europe, the government calculates the percentage of low carbon emission cars in the whole car production portfolio. When the percentage of low carbon emission vehicles is calculated, the relaxed threshold can also be calculated. This threshold is relaxed as a percentage on top of the current year's CO_2 emission threshold. To calculate the percentage of the relaxed threshold, the percentage of the low carbon emission portfolio should first be compared to the regulated percentage set for low carbon emission vehicles for each year.

Mathematical Formulation for Super Credit System in Europe

The detailed model is listed below. Equation (19), with the help of Equations (20) and (21 3.21), represents the calculation of the relaxed threshold based on the production portfolio. Equations (20) and (21) set a lower limit with the help of the big number M, and Equation (22) sets the upper limit. Afterwards, the following equation incorporates the relaxed threshold percentage into the emission portfolio. This model will be further linearized for solving, and a detailed description of the linearized model can be found in Section 4.

$$\frac{\sum_{v\in\{V:E_v\leq\sigma_{low}\}}(q_{vt}\cdot(1-\frac{\gamma_{mutiplier}}{\sigma_{low}}\cdot E_v))}{\sum_{v\in V} q_{vt}} \geq P_t^{relax}+P_t^{EVthres}-M\cdot(1-y_1) \qquad \forall t\in P \quad (19)$$

$$P_t^{relax}\geq -M\cdot y_1 \qquad \forall t\in P \quad (20)$$

$$P_t^{relax}\leq M\cdot y_1 \qquad \forall t\in P \quad (21)$$

$$P_t^{relax}\leq P^{SuperMax} \qquad \forall t\in P \quad (22)$$

$$E_t^{law}\cdot(1+P_t^{relax})\geq E_t^{Relaxlaw} \qquad \forall t\in P \quad (23)$$

$$\sum_{v\in V}(E_v\cdot q_{vt})\leq E_t^{Relaxlaw}\cdot(1+\theta)\cdot\sum_{v\in V}q_{vt} \qquad \forall t\in P \quad (24)$$

$$z_t^{penalty}\geq(\sum_{v\in V}(E_v\cdot q_{vt})-E_t^{Relaxlaw}\cdot\sum_{v\in V}q_{vt})\cdot c^{CO_2} \qquad \forall t\in P \quad (25)$$

$$z_t^{penalty}\geq 0 \qquad \forall t\in P \quad (26)$$

3.4.2. Dual Credit System in China

In China, the policy for encouraging the production of low-carbon emission vehicles differs from that in the EU. It is a dual-sided policy. Instead of setting a threshold with some relaxation criteria, the Chinese government has established a credit system for CO2 emissions. For a car production company, two different credit scores are calculated: Corporate Average Fuel Consumption (CAFC) and New Energy Vehicle (NEV) credits.

The CAFC credit score is more focused on the fuel consumption of the car portfolio, with a higher score for companies producing more traditional cars. The CAFC score has a target score calculated based on the current number of fuel consumption cars produced, as described in Equation (28). The coefficient is based on the size of the car and is calculated according to the vehicle's weight. The actual CAFC score is calculated based on the actual fuel consumption of the vehicle type, divided by a weighted factor based on the vehicle's powertrain technology type, as described in Equation (3.29). The final CAFC score is the difference between the standard CAFC score and the actual CAFC score.

For the NEV credit score, there is also a target score and actual score calculation, but the focus is on low-emission vehicles. The target score, which is also the standard NEV score, is calculated based on the quantity of ICEV cars with a coefficient of the target ratio for each year, as described in Equation (32). The actual NEV score is calculated based on the number of low carbon emission vehicles (PHEV, BEV, and FCEV) produced, with different coefficients for different types of vehicles, as described in Equation (31). Based on the policy regulated in 2020, the coefficients vary according to the model of the low carbon emission vehicle based on factors such as electric range multiplier (ER), battery energy density multiplier (BD), electric energy consumption multiplier (EC), and rated power multiplier (RP).

Once both the CAFC and NEV scores are obtained, the Chinese government requires car manufacturers to balance the two scores, which can be freely traded with banks or other companies. The modeling process for this exchange is complicated, so this model uses a monetary value to simulate the market exchange process. This means that car manufacturers could gain money as profit with more NEV credit scores earned and lose money with more CAFC scores.

Mathematical Formulation for Dual Policy in China

In this scenario, no additional constraints are required. However, for the objective function, the penalty cost would be replaced by the dual credit score, which consists of a CAFC credit score and a NEV credit score. The sum of these two scores would contribute to the final objective function, with a positive value indicating capital gain and a negative value representing a penalty cost. The monetary value of the score is based on the market price, but for simplicity in this model, the price of the score is assumed to be constant, based on past average values. This factor will be further discussed later.

CAFC SCORE

$$CAFC_t = S_t^{CAFC} - A_t^{CAFC} \qquad \forall t \in P \quad (27)$$

with

$$S_t^{CAFC} = \sum_{v \in V} (S_{vt}^{FC} * q_{vt}) \qquad \forall t \in P \quad (28)$$

$$A_t^{CAFC} = \sum_{v \in V} (\frac{A_{vt}^{FC}}{W_v^{FC}} * q_{vt}) \qquad \forall t \in P \quad (29)$$

NEV SCORE

$$NEV_t = A_t^{NEV} - S_t^{NEV} \qquad \forall t \in P \quad (30)$$

with

$$A_t^{NEV} = \sum_{v \in V:[BEV,PHEV,FCV]} (k_v * q_{vt}) \qquad \forall t \in P \quad (31)$$

$$S_t^{NEV} = \sum_{v \in V:[ICEV]} (R_t * q_{vt}) \qquad \forall t \in P \quad (32)$$

FINAL DUAL CREDIT SCORE

$$D_t^{Dual} = (CAFC_t - NEV_t) * C^{DualCredit} \qquad \forall t \in P \quad (33)$$

3.4.3. Credit System in US

In the United States, although there exists a CO_2 credit system, it is important to note that this system is only in place in the state of California. In the rest of the United States, there are federal vehicle emissions standards that car manufacturers must adhere to. These federal standards require car producers to ensure that their vehicle manufacturing portfolio strictly follows the restrictions for the average CO 2 emission of the fleet.

Mathematical Formulation for Emission Regulation in US

Under the U.S. emission law, an additional constraint (34) needs to be added to ensure that the carbon emissions for each year's production portfolio are strictly below the average emission standard set.

$$\sum_{v \in V} (E_v * q_{vt}) \leq E_t^{law} * \sum_{v \in V} q_{vt} \qquad \forall t \in P \quad (34)$$

4. Solution approach

This section present the solution approach for solving the optimization model. For the Chinese and US credit systems the optimization model is a mixed-integer linear program, which can be solved directly by a commercial solver. However, the EU credit system requires the non-linear constraints in equation (19), (24) and (25). Hence, to solve the model it must be linearized first. The proposed linearization approach is detailed in the following.

4.1. Linearization Approach

The original model for the super credit system in Europe introduces several non-linear constraints to the original model, making it unsolvable by standard solvers. The primary issue arises from the presence of the decision variable q_{vt} in both the numerator and denominator of constraint (19) in the original problem. Furthermore, constraints (24) and (25) involve the multiplication of the decision variable $E_t^{Relaxlaw}$ by q_{vt}. To solve this model, we need to transform the decision variable q_{vt}.

Using traditional methods, such as introducing new binary variables or using precewise linear function to replace the decision variable q_{vt} proves to be too complex for linearizing the model. This complexity arises because the decision variable q_{vt} appears in numerous instances throughout the model. Moreover, the decision variable q_{vt} exhibits a high degree of flexibility in terms of its range and value, as more than 120 decision variables must be determined over a 10 -year period. Achieving an optimal solution using conventional techniques would demand a significant amount of computational time. Since the primary goal of this paper is not to attain optimality, this paper employs an estimation approach instead. This approach allows me to find a heuristic solution that closely approximates the optimal solution, providing a practical resolution to the problem.

The approach functions in the following manner. Initially, I address the optimization problem without incorporating the relaxed policy, which solely consists of a threshold for fleet emissions and associated penalty costs. Subsequently, I reintroduce the relaxation aspect into the solution obtained in the previous step, thereby generating a heuristic solution for the European super-credit system. By utilizing this estimation approach, I can navigate the complexities introduced by the super credit system model and make informed decisions that align with the overarching objectives of the study. Detailed justification and implementation of this solution are presented in the following.

4.1.1. Mathematical Formula of the Linearized Model

In this linearized model, constraint (19) is redefined and substituted with constraint (35). The variable q_{vt} in the denominator is replaced with $P_{\min} * \sum_{m \in M} d_{mt}$, where $P_{\min}$ is an adjustable parameter used to estimate the total production volume. Additionally, constraint (42) is introduced to ensure that the total production volume exceeds the estimated production quantity in the planning period after 2025, as the capacity is fixed starting from the year 2025 and cannot be altered. The replacement of the decision variable q_{vt} also applies to constraints (24) and (25), which are replaced by constraints (40) and (41). Through this approach, q_{vt} is transformed into a parameter that can be adjusted using P_{min}, making the problem solvable for the purpose of testing the results. The detailed formulation of the model is described below.

$$\frac{\sum_{v \in \{V: E_v \leq \sigma_{low}\}} (q_{vt} \times (1 - \frac{\gamma_{mutiplier}}{\sigma_{low}} \times E_v))}{P_{min} \cdot \sum_{m \in M} d_{mt}} \geq P_t^{relax} + P_t^{EVthres} - M \cdot (1 - y_1) \qquad \forall t \in P \quad (35)$$

$$P_t^{relax} \geq -M \cdot y_1 \qquad \forall t \in P \quad (36)$$

$$P_t^{relax} \leq M \cdot y_1 \qquad \forall t \in P \quad (37)$$

$$P_t^{relax} \leq P^{SuperMax} \qquad \forall t \in P \quad (38)$$

$$E_t^{law} \times (1 + P_t^{relax}) \geq E_t^{Relaxlaw} \qquad \forall t \in P \quad (39)$$

$$\sum_{v \in V} (E_v \cdot q_{vt}) \leq E_t^{Relaxlaw} \cdot (1 + \theta) \cdot P_{min} \cdot \sum_{m \in M} d_{mt} \qquad \forall t \in P \quad (40)$$

$$z_t^{penalty} \geq (\sum_{v \in V} (E_v \cdot q_{vt}) - E_t^{Relaxlaw} \cdot P_{min} \cdot \sum_{m \in M} d_{mt}) \cdot c^{CO_2} \qquad \forall t \in P \quad (41)$$

$$\sum_{v \in V} q_{vt} \geq P_{min} \cdot \sum_{m \in M} d_{mt} \qquad \forall t \in P_{2025} \quad (42)$$

$$z_t^{penalty} \geq 0 \qquad \forall t \in P \quad (43)$$

4.1.2. Evaluating the Quality of the Approximation

By performing this replacement, the objective function becomes prone to overestimation, as the new variable $P_{\min} * \sum_{m \in M} d_{mt}$ will always be smaller than the actual production quantity q_{vt}. The parameter $P_{\min}$ is constrained not to fall below 70% because it is essential to maintain a reasonable production volume, and excessively low production quantities are impractical. The gap between the overestimated result and the real result can be analyzed and compared in order to search for a heuristic solution that closely approximates the optimal solution. If the estimation leads to a local minimum with a lower gap and a high objective value, it suggests that the optimal solution might fall within this production quantity range.

For the gap analysis, P_{min} is tested within a range from 70% to 100%, with intervals of 5%. The model is initially solved by setting the $P_{\min}$ value to obtain the real production quantity. Subsequently, the actual production quantity is reintroduced into the original problem to calculate the actual NPV value. Both results are collected and recorded for further analysis.

The observed gap is approximately 2%, and it shows relatively little fluctuation. Additionally, a peak objective result is observed at the point where the $P_{\min}$ value is set to 90% with the lowest gap. Detailed graphical representation can be found in Appendix (see Figure A.1). Based on these results, it is reasonable to assume that the optimal solution may fall within this range, but a more precise estimation is required.

For this refined estimation, the testing range is narrowed to 90% to 100% but with a higher interval frequency of 1%.

A detailed graph has been generated, and according to this graph (see Figure A.2), 91% is the estimated point with the highest objective value and the lowest gap. However, using this estimation method, the quantity produced in each year of the planning period is nearly identical, making it challenging to perform tests to find the exact optimal solution. To interpret the 91% estimation, a relaxed model including the Europe emission policy but excluding the Super credit relaxation needs to be established. For this model, the constraint of the super credit policy is excluded, and the additional emission related constraints used is described below with only the fleet emission threshold along with the penalty cost.

$$\sum_{v\in V}(E_v \cdot q_{vt}) \leq E_t^{law} \cdot (1+\theta) \cdot \sum_{v\in V} q_{vt} \qquad \forall t \in P \quad (44)$$

$$z_t^{penalty} \geq (\sum_{v\in V}(E_v \cdot q_{vt}) - E_t^{law} \cdot \sum_{v\in V} q_{vt}) \cdot c^{CO_2} \qquad \forall t \in P \quad (45)$$

$$z_t^{penalty} \geq 0 \qquad \forall t \in P \quad (46)$$

This linear model can be solved, and the results indicate that the optimal average output production quantity over a ten-year production horizon is also around 91%, which closely aligns with the estimated $P_{\min}$ value. Furthermore, when the credit relaxation is applied back to the resulting production quantities, the objective value increases by approximately 2% with a higher net NPV value. These results suggest that this revised model, excluding the super credit relaxation, could serve as a starting point for calculating a satisfactory heuristic solution. To assess the reliability of these results, the same analysis is repeated for a different demand scenario, assuming that the market is more innovative and people are more receptive to low carbon emission vehicles. The detailed result graphs are provided in Appendix A. 3 and A. 4.

The results show that the production quantity at approximately 86% corresponds to the highest objective value and the lowest result gap, with a difference of about 1.67%. For the revised model without the super credit relaxation, the optimal production quantity is around 84%, which is also close to the estimated result. It also yields the highest objective value, at a level of approximately 2% higher than the estimated result.

4.1.3. Approximation Approach used for Experiments

In conclusion, the revised model, which excludes the super credit relaxation, has undergone testing for reliability and sensitivity by varying the production quantity within a range of -5% to 5% in both conservative and innovative demand scenarios. Subsequently, the super credit relaxation policy was reintroduced to obtain the final results. The detailed graphs in the Appendix (see Graph A. 5 and A.6) demonstrate that this revised model consistently yields the largest objective value locally.

As a result, it can be concluded that solving the super credit system model can be performed in two phases. First, utilize the model without the relaxation policy as the initial estimation. Then, reintroduce the relaxation policy to obtain the final heuristic result. While this result may not be optimal, it is sufficiently close to the optimal solution for further analysis.

5. Design of Experiment

This section outlines the experimental design for the computational study of the different emission policy model. In Section 5.1, the foundational data for modeling the system under distinct policy frameworks is introduced. Sections 5.2 and 5.3 detail the procedures used to analyze the the impact of the different policies and their parameters.

5.1. Test Instances

First, in Section 5.1.1, I present a detailed description of the data and specifications for the base model. This base model excludes the effects of the emission policy system and provides specific numerical values for various parameters based on personal assumptions and research. Second, in Section 5.1.2, I provide specific numerical values for different parameters within various emission policies in Europe, China, and the U.S.

5.1.1. Test Instances for the Base Model

The data originates from a passenger car manufacturing company in Europe. It is derived from publicly available data sets with same source used in the Thiel et al. (2016) paper, supplemented with certain assumptions and settings based on personal research.

Vehicle Projects

A total of 264 vehicle projects have been defined spanning from the year 2025 to 2035. These vehicle types are categorized based on powertrain technology (ICEV, PHEV, FCEV, BEV). Furthermore, within each powertrain technology category, they are further classified by power range, including 'small,' 'medium,' and 'large,' as well as discrete power levels, denoted as 'high' or 'low.' It's important to note that FCEV and BEV vehicles are considered zero-emission vehicles, while PHEVs are classified as low-emission vehicles. Additionally, for ICEV vehicle types, it is assumed that advancements in technology will lead to a reduction in their pipeline emissions, as is the case for PHEVs. Conversely, it is assumed that variable production costs for ICEVs and PHEVs will increase in the future.

The sale revenue for each vehicle project varies depending on the year, size, and powertrain technology, falling within a range of € 8,400 to € 28,000. Furthermore, each vehicle project is assumed to have a life cycle of seven years. The development cost for each vehicle project is assumed to be uniform and approximately € 420 million. More detailed information can be found in the Data Information Excel File.

Production Resources

For different discrete power levels ('high' or 'low'), the same set of resources can be utilized. In terms of production resources, the capacity required to meet the production plan can be increased annually. However, increasing capacity entails a fixed cost of €20 million, and each incremental unit of capacity incurs a variable cost of € 2.75 as part of the ramp-up process. It's important to note that during the rampup period, only 75 % of the total capacity for that year can be effectively utilized. In addition to production variable costs, there is also an additional fixed cost of € 50 associated with each vehicle produced.

Vehicle Demand

The total assumed demand for vehicles is 2.25 million units per year, spanning from 2025 to 2035. It's important to note that the total demand remains constant over this ten-year planning period. However, the market share for the four types of vehicles will vary. Each year, the percentage split for each powertrain technology is assumed to remain unchanged. In this model, I consider two distinct demand scenarios categorized into two main groups: 'innovative' and 'conservative.' Figure 2 illustrates these two demand levels.

In both scenarios, ICEVs dominate the market share, starting at about 75 %, and gradually decrease their market share as PHEVs, BEVs, and FCEVs gain ground. In the 'innovative' scenario, I have a more optimistic outlook on electric cars (BEVs and FCEVs) and assume that the market will be more accepting of them. As a result, the market share for these powertrains increases linearly each year at a higher rate compared to the 'conservative' scenario. Conversely, in the 'conservative' scenario, I assume that people will be more cautious in adopting purely electric cars, so the market share of PHEVs may increase more rapidly.

Overall Manufacturing Settings

In this model, the objective value NPV was evaluated at a discount factor of 5% each year, and the final objective function is based on the year 2025. Additionally, for the allocation of the increased capital expenditure, it is assumed that the spending is evenly distributed over 7 years. Furthermore, the vehicle projects are determined in the years leading up to 2025, specifically from 2020 to 2024, and the capacity can only be changed in 2025. All constant parameters are summarized in Table 4, with further data available in the Data Information Excel File.

Table 4: Constant Parameter Values

Constant Parameters Value		
Parameter	Unit	Value
t^{max}	years	7
c_v^{RD}	€	420 Million
$c^{RampUpFixed}$	€	20 Million
$c^{RampUpVar}$	€ / (car × year)	2.75
$c^{Resource}$	€ / (car × year)	65
i	%	5
θ^{max}	%	95
SOP^{max}	vehicle projects	15
q^{min}	cars	1 Million

5.1.2. Test Instances for the Different Policy System

The data is sourced from regulatory documents. This information is presented in different sections dedicated to the different policy systems.

Super Credit System

For the test instance used in modeling the super credit system, the information is sourced from the official website of the European Union (European Commission, 2023). The emission threshold from 2025 to 2029 is set at approximately 80 g/km, and by 2030, it is reduced to 60 g/km. Further reductions occur by 2035 when the threshold is set at 45 g/km. In the event of exceeding the carbon emission limits, the government would impose a penalty cost of € 95 per unit of excess emissions (g/km) for each vehicle sold.

For the relaxed percentage of the low carbon emission vehicle, the current regulation stipulates that from 2025 to 2029, car producers must exceed a minimum of 15 % in low carbon emission vehicles to qualify for the relaxed threshold. From 2030 to 2035 , this percentage requirement increases to 35 %. Additionally, the maximum allowed increase for the threshold relaxation is 5 % per year. For example, in 2030, if a car manufacturer achieves a 38 % production of low carbon emission vehicles, the relaxed threshold percentage would be 3 %. If the low carbon emission vehicle production further increases to 45 %, the manufacturer would receive the maximum 5 % relaxed percentage. Table 5 provides a summary of the parameters for the super credit system, and the mathematical formulation of the super credit system is detailed in the section below. Also when calculating the percentage of low carbon emission vehicles, the coefficient of low emission vehicles in the numerator is linearly dependent on the actual carbon emissions. With the inclusion of the PHEV multiplier in the current policy setting, vehicles with 50 g/km carbon emissions would start with a coefficient of 0.3 and increase linearly as carbon emissions decrease. For example, a zero-emission vehicle would have a coefficient of 1 , representing

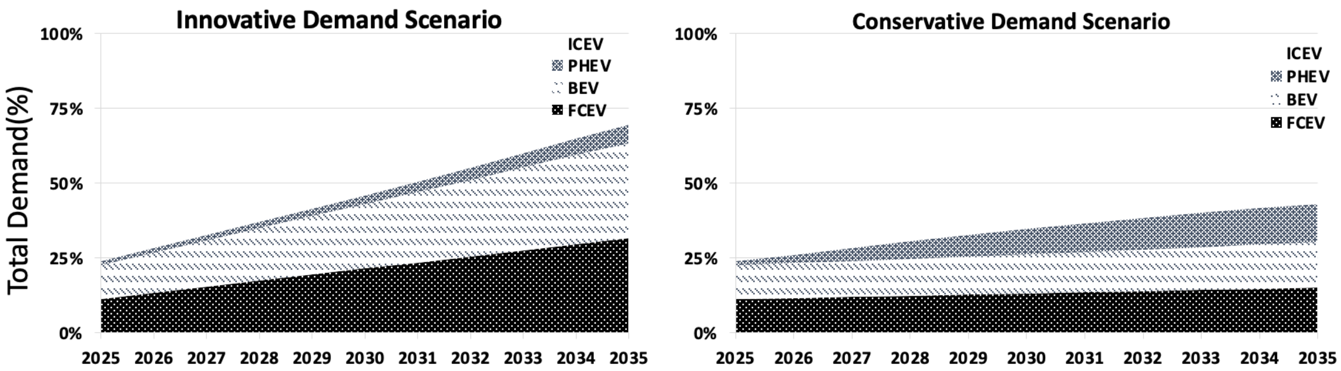


Figure 2: Vehicle Demand

Table 5: Super Credit System Parameters in Europe

Super Credit System Parameter Values			
Factors	Symbol	Unit	Value
Emission threshold	E_t^{law}	g/km	80-60-45
Fleet emissions limit for low emission vehicle	σ_{low}	g/km	50
Penalty cost	c^{CO_2}	€ / (g/km)	95
Relaxed threshold before 2030	$P_t^{EVthres}$	Percentage	15%
Relaxed threshold after 2030	$P_t^{EVthres}$	Percentage	35%
Maximum relaxed threshold limit	$P^{SuperMax}$	Percentage	5 %
PHEV multiplier	$\gamma_{mutiplier}$	-	0.7

one car produced, while a car with 25 g/km emissions would have a coefficient of 0.65.

Dual Credit System

For the test instances of the dual policy system in this model, the policy information is referenced from a report by the ICCT (International Council for Clean Transportation) (International Council on Clean Transportation (ICCT), 2016).

Regarding the target values for the CAFC score represent in Equation (28), fuel consumption vehicles are categorized into three groups (low, medium, large). The standard values S_{vt}^{FC} are determined by applying the weight of each vehicle size to the Chinese government's fuel consumption standard formula (TransportPolicy.net, 2018). Furthermore, after 2030, the Chinese government plans to further reduce the standard from an average of 4.0 $L/100\ km$ to 3.2 $L/100\ km$, resulting in lower fuel consumption standards for vehicles of different sizes (International Energy Agency (IEA), 2021). The resulted final consumption standards are detailed in Table 6.

For the actual CAFC score calculation represent in Equation (29), the value is converted from the carbon emission value. The actual coefficient A_{vt}^{FC} for fuel consumption is expressed in units of $L/100\ km$. The conversion from g/km

Table 6: Fuel Consumption Standard for Different Vehicle Sizes (2025-2035)

Fuel Consumption Standard (2025-2035) $[L/100\ km]$			
Size	Weight	Before 2030	After 2030
Small	680 kg	3.6	2.88
Medium	1500 kg	4.05	3.22
Large	1995 kg	4.398	3.518

to $L/100\ km$ is given by 100 $g/km = 4.25\ L/100\ km$. Additionally, since the data is sourced from an EU country and the measurement system differs, the Chinese government would consider about a 15% adjustment (Tietge et al., 2017). Therefore, the final actual fuel consumption should be multiplied by a factor of 1.15. Equation (5.1) provides a simple example of the conversion calculation. Furthermore, for the weighted factor W_v^{FC} in calculating the actual CAFC score, it is set to 1 for all types of vehicles in accordance with current regulations.

$$100(g/km) = 4.25 \times 1.15 = 4.8875(L/100km) \quad (47)$$

For the target NEV score calculation is represent in Equation (32). As for the target ratio R_t, it can vary from year to year. In 2025, the target ratio is approximately 20%, increasing to 40% by 2030, and eventually reaching 50% by the end of 2035. The target ratio can be adjusted each year, although there are no official rules announced. In this model, the target ratio is assumed to increase linearly and evenly each year, with specific percentages detailed in Table 7.

Table 7: NEV Target Ratios for the Years 2025-2035

NEV Target Ratio (2025-2035) [%]	
Year	Target Ratio
2025	20%
2026	24%
2027	28%
2028	32%
2029	36%
2030	40%
2031	42%
2032	44%
2033	46%
2034	48%
2035	50%

The formula for the calculation of the actual NEV score is in Equation (31). The weighted factor k_v for the calculation of the actual NEV score could be hard to predict since the value is different for specific vehicle model, to simply the model, this model use the average score value and shown in table 8.

Table 8: NEV Credits per Vehicle Type

Weighted Factor per Type	
Vehicle Type	Estimated NEV Credit
PHEV	1.6
BEV	4
FCEV	4.8

For the monetary value $C^{DualCredit}$, in Chen and He (2022) article, the average exchange cost for one credit is between $2600-2900$ RMB, so in this model it is assumed to be 330 Euro after the currency exchange.

U.S. Emission Policy

The detailed emission threshold values E_t^{law} in Equation (34) used in the US emission model are sourced from the standard released by the US Environmental Protection Agency (Register, 2023) and are summarized in Table 9. To maintain consistency and precision, the units in the policy, originally given in units of $g/mile$, have been converted to units of g/km, with values rounded to one decimal digit.

5.2. Policy Comparison Experiment

This paper aims to employ mathematical models to explore the differences among three distinct emission policies in Europe, China, and the US, while comparing them to the baseline model with no emission policy in place. The results will be evaluated under two different demand scenarios: conservative and innovative demand. Each policy's parameters have been calculated and estimated based on publicly available information.

For each policy scenario and demand type, a comprehensive analysis will be conducted, including an examination of the vehicle initialization schedule and production quantities. Additionally, beyond the decision variables, the objective function will be thoroughly examined. This examination will encompass cost structures and average fleet emissions to gain insights into the impact of various emission policies. Table 10 summarizes the experiment's outline.

5.3. Sensitivity and Factorial analysis for Different Emission policies

In addition to comparing different emission policies, this paper will also conduct sensitivity and factor analyses for each emission policy to assess how policy parameters affect policy effectiveness and identify the parameters with the most significant impact on emission policies. For sensitivity analysis, each factor will be categorized into three levels: low, basic, and high, and tests will be conducted at these levels for analysis. In the factorial analysis, a 2-level factorial analysis will be performed, reducing each factor to two levels: high and low. A 1/2 fraction of the full factorial design method will be used to enhance the efficiency of the factorial analysis.

For the analyzed outputs, due to the extensive testing required, only two types of outputs will be compared: the net total NPV (Net Present Value) and the percentage of low carbon emission vehicles. NPV is the objective function favored by car manufacturers, as they seek to maximize NPV. However, this objective may conflict with the the reduction of carbon emissions. Therefore, the percentage of low carbon emission vehicles will also be analyzed to assess the policy's impact on social benefits from the government's perspective and evaluate policy effectiveness. Table 11 summarizes the Design of Experiment (DOE) for the emission policy.

5.3.1. Super Credit System

For the Super Credit system policy in Europe, four factors will be considered for the analysis. The first factor is the demand type, which includes two scenarios: conservative and innovative. The next factor is the threshold percentage for relaxation, which is defined as the percentage of low emission vehicles with less than 50 g/km emissions. The threshold is set in two stages, one before 2030 and one after 2030.

Table 9: Federal Vehicle Emissions Standards

Year								
	2025	2026	2027	2028	2029	2030	2031	2032 and later
Emission standard (g/km)	149	152	134	116	99	91	82	73
Emission standard (g/km)	92.9	94.8	83.5	72.3	61.7	56.7	51.1	45.5

Table 10: Comparison of Different Policy Experiments

Policy Comparison Experiment		
Policy Type	Demand	Output
Super Credit System	Con/Inno	• Vehicle initialization schedule • Vehicle production quantity • Cost structure • Average fleet emission result
Dual Credit System	Con/Inno	
US Credit System	Con/Inno	
Baseline Model (No emission policy)	Con/Inno	

For the sensitivity analysis, the range of the threshold before 2030 is from set at level 5%, 15% and 25%, and after 2030, it is at the level of 25%, 35% and 45%. The third factor is the maximum allowed threshold percentage, which is at the level of 1%, 5% and 9%. Finally, the PHEV multiplier, which provides a base percentage for PHEV-type vehicles, is included in the analysis. It can be set to either "on" or "off" to test its effect on NPV value and the actual quantity of low carbon emission vehicles. These factors will be analyzed to understand their impact on the NPV value and the quantity of low carbon emission vehicles.

5.3.2. Dual Credit System

In the China dual credit system, four factors will be considered for analysis. The first factor is the demand type, which is similar to the super credit system. The remaining three factors are tested by percentage changes, and they include one important indicator for calculating the CAFC score, one indicator for the NEV score, and one factor considering the exchange cost for credit score realization. The level of change for these factors is the same which are -50%, 0% and 50%. These factors will be analyzed to understand their impact on the NPV value and the quantity of low carbon emission vehicles.

5.3.3. US Credit System

For the US credit system, apart from the demand type factor, one more factor which is the percentage change of regulated threshold are considered at level of -10%, 0% and 10%. Also strict or non-strict compliance would be tested as another factor in this scenario. For strict compliance meaning that the threshold could not be exceed and non-strict compliance it is assumed the penalty cost would be similar in EU with 95 €/((g/km) × year).

6. Result

To assess the impact of various policy systems, Section 6.1 includes an analysis of the optimal production plan under four different policy scenarios. Additionally, the consideration of a multitude of parameters comes into play, with each having the potential to influence the final outcomes of these regulations. For this purpose, Section 6.2 conducts sensitivity analysis at three different levels (low, basic, and high) for selected parameters under different policies, while Section 6.3 performs a factor analysis of these parameters.

6.1. Optimal Production Plan

The detailed plan includes the initialization of vehicle projects for each year from 2025 to 2035 , as well as the production quantity for four different types of powertrain technologies.

In the vehicle project initialization section, the blocks are separated by powertrain technology, vehicle project size, and year. Gray blocks represent the start of a powertrain technology in that year, while white blocks indicate that the vehicle project will not be initiated. For the production quantity, each year from 2025 to 2035 is categorized by powertrain technology and filled with different patterns, as described in the stacked bar chart.

Additionally, the average fleet emissions for each year were plotted on a line chart, with the EU-regulated fleet emission threshold as a reference for comparison. The objective value, composed of six main components [Capacity income at the end of the period, Capacity increase cost, Development cost, Profit, Fixed cost, Penalty cost/Dual Credit value], was depicted in a bar chart. The final Net Present Value (NPV) was shown on a line chart for further analysis. These visualizations provide insights into the different policy scenarios and their effects on production planning and emissions.

Table 11: Summary of Design of Experiments (DOE) for Emission Policy

Summary for DOE of Emission Policy				
Policy Type	Factors	Level	Type	Outputs
Super Credit System	Demand Type	ConInno	Option	NPV, EC percentage
	Relaxed Threshold	Before 2030 [5% or 25%] After 2030 [25% or 45%]	Percentage	
	Maximum Threshold	1% or 9%	Percentage	
	PHEV Multiplier	Y/N	Option	
Dual Credit System	Demand Type	Con/Inno	Option	NPV, EC percentage
	% change of Standard Fuel Consumption	-50% or 50%	Percentage	
	% change of exchange price	-50% or 50%	Percentage	
	% change of NEV weight factor	-50% or 50%	Percentage	
US Credit System	Demand Type	Con/Inno	Option	NPV, EC percentage
	% change of CO_2 threshold	-10% or 10%	Percentage	
	Strict compliance	Y/N	Option	

Table 12: Parameter Changes for Dual Credit System

Dual Credit System Parameter Changes			
	Standard Fuel Consumption (CAFC)	Exchange Price	NEV Weighted Factor (NEV)
Example Base (small_PHEV_low_2025)	3.6	€330	1.6
-50% Percentage Change	1.8	€165	0.8
+50% Percentage Change	5.4	€495	2.4

Table 13: Parameter Changes for US Credit System

US Credit System Parameter Changes								
Year	2025	2026	2027	2028	2029	2030	2031	2032 and later
Emission standard (g/km)	92.9	94.8	83.5	72.3	61.7	56.7	51.1	45.5
-10% Percentage Change	83.6	85.3	75.2	65.1	55.5	51.3	36.0	41.0
+10% Percentage Change	102.2	104.3	91.9	79.5	67.9	62.4	56.2	50.1

6.1.1. Conservative Demand

The following results were calculated under the assumption of a conservative market demand for low-emission vehicles, characterized by a lower growth rate in low-emission vehicle adoption. This scenario represents a more cautious market approach towards low-emission vehicles.

Detailed Portfolio Analysis

Figure 3 presents information for the four different emission policies. In the scenario of no emission system, which can be considered a reference point for interpreting the other three policies, there are no penalties or restrictions on excess fleet emissions. In this scenario, only vehicle projects that contribute positively to the net present value of the portfolio are initiated. From this scenario, it is evident that all types of ICEV vehicles in each year have a positive effect on the profit margin. However, for the small-sized PHEV, FCEV, and BEV vehicles, the profit margin is consistently negative, so there is no incentive for manufacturers to produce these vehicle projects. For medium and large-sized vehicles in these powertrain technologies, as production costs are assumed to decrease due to technological development, medium and large-sized PHEV projects are initiated after 2029, medium-sized FCEV projects after 2031, large-sized FCEV projects after 2029, and all medium and large-sized BEV projects are initiated due to their positive profit margins.

After analyzing the base scenario with no impact from emission policies, three different major policies can be analyzed. Figure 3 shows that several vehicle types with negative profit margins are initiated in order to balance penalty costs or meet the constraints on excess fleet emissions. The Dual Credit Policy results in the lowest number, with about 70 initiated low-emission vehicle projects during the ten-year planning period. It is followed by 76 vehicle projects in the Super Credit System, while the US Credit System leads with the highest number, with about 87 initiated projects. ICEV vehicles dominate the portfolio, but in the US Credit System, due to strict emission standards after 2029, small-sized ICEV vehicles are terminated because of lower profit margins compared to medium and large-sized ICEV vehicles. For PHEV types, in the US Credit System, several small-sized PHEV projects are initiated to meet emission constraints. However, in the Super Credit System and Dual Credit System, no small-sized PHEV projects are initiated. Furthermore, at the end of 2035, in the Super Credit System and US Emission System, there is a sudden drop in the number of large-sized PHEV projects, likely due to the sufficient production of zero-emission vehicles. For these projects, the profit margin decreases, potentially falling below that of zero-emission vehicle types due to increased production costs. For FCEV and BEV types of vehicles, medium and large-sized versions are initiated to balance the high CO2 emissions from ICEV vehicles, and small-sized versions are initiated as a last resort. In comparison, BEV projects are more favorable for manufacturers due to their higher profit margins.

Regarding production quantities, it is evident that manufacturers tend to align with market demand and produce as many ICEV vehicles as possible. Comparing the results to the base model with no emission policy, it can be observed that all three emission policies would reduce the production quantity of ICEV vehicles, with the US Emission Policy leading to the largest reduction. In the Super Credit System, there is a sudden drop in the production of ICEV vehicles at year 2035. This drop is a result of the fleet emission threshold decreasing from 60 g/km to 45 g/km, causing manufacturers to reduce production to meet the stricter standards. For the Dual Credit Policy, the initial production quantity in 2025 is lower due to lower demand for low-emission vehicles and the lower fuel efficiency of ICEV vehicles. However, in the following years, production quantities increase since the ICEV vehicle become more fuel efficient thus turns out to become more favorable in the dual credit score system.

Fleet Emission and NPV Analysis

The fleet emissions and objective function composition for the four different policy scenarios are depicted in Figure 4. The red line represents the EU-regulated threshold for average CO_2 fleet emissions and serves as a reference to assess the impact of different emission policies. In the base model, shown by the black line, there is some decrease in fleet emissions due to technology development, but the average CO_2 fleet emissions consistently remain above the EU threshold meaning some regulation need to be performed as an external force to control the fleeting emission. The three different emission policies all have some effect on reducing fleet emissions in each year. In the Super Credit System (blue line), fleet emissions follow the EU-regulated threshold with some relaxation in certain periods. In the Dual Credit System (yellow line), the trend is similar to the line with no emission policy but with smaller absolute fleet emissions. However, fleet emissions are still above the EU-regulated threshold. Lastly, in the US Emission System (green line), fleet emissions strictly follow the US emission threshold, which becomes more stringent after 2028.

In terms of net present value, the base scenario yields the highest number. In the Dual Credit Policy, the NPV is also high because manufacturers can earn money for producing low-emission vehicles. Under conservative demand, manufacturers would decide to produce more low-emission vehicles to earn these new vehicle credits that could be trade to earn some money. In the Super Credit System, a minor amount of penalty cost is incurred, resulting in a 12% decrease in the net present value compared to the base model. The US Emission System yields the lowest net present value, as targets must be strictly met, leading to the production of several low-profit-margin vehicle types and a 25% decrease in the objective value.

6.1.2. Innovative Demand

In the Innovative demand scenario, the market is more receptive to low-emission vehicles, with a higher growth rate in the low-emission vehicle market.

Detailed Portfolio Analysis

In this demand scenario, the market introduction of new vehicle project is similar but with some minor differences, as described in Figure 5. In the baseline situation, medium-sized FCEV projects in 2030 would also be initiated due to higher demand, and the large-sized BEV vehicle project in 2025 would not be started to prioritize the production of ICEV types. Compared to the conservative demand scenario,

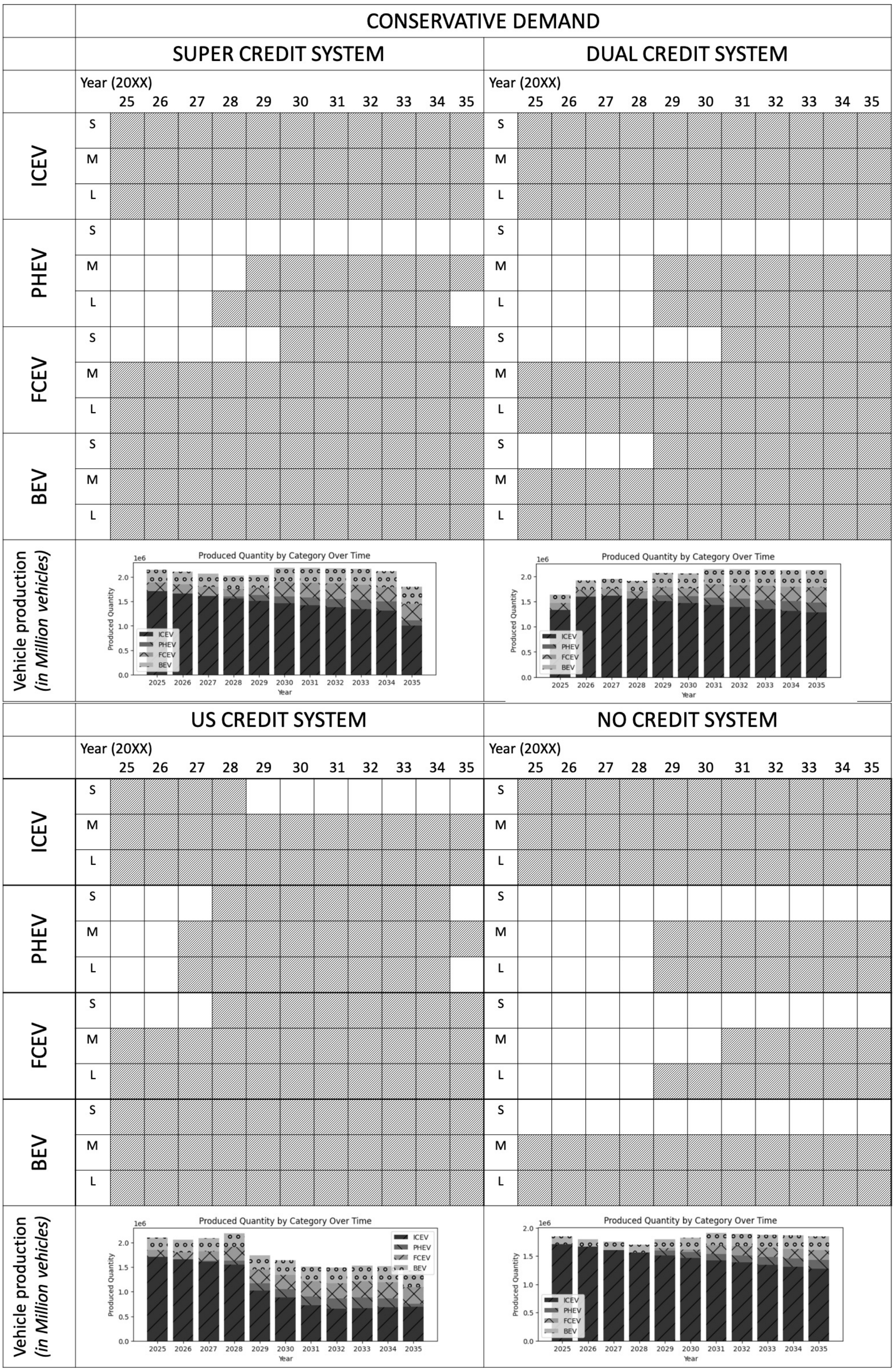
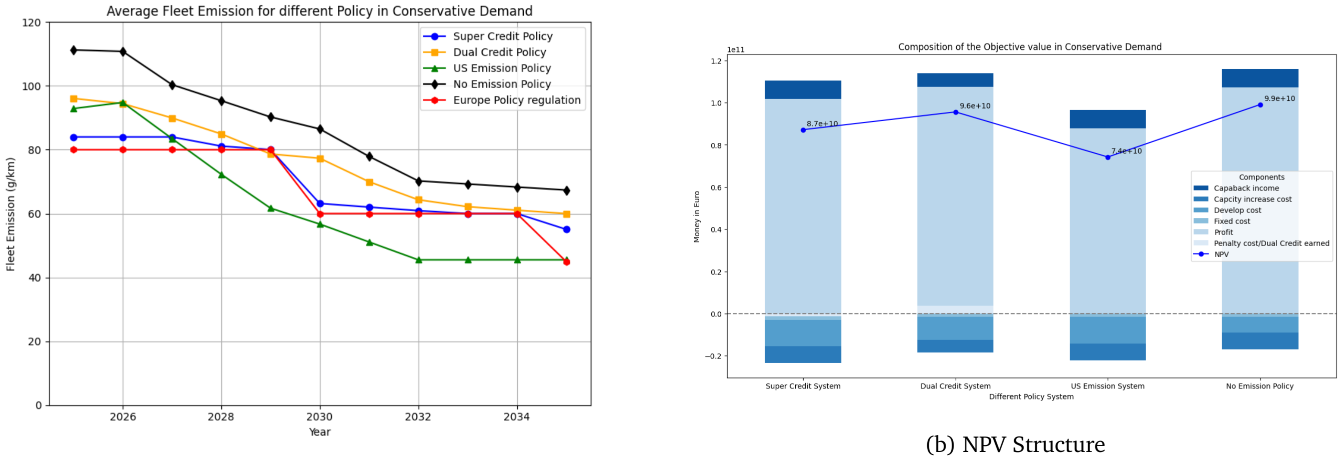


Figure 3: Optimal Portfolio for Different Policy in Conservative Demand

for all three policy scenarios, manufacturers would initialize a lower quantity of low-emission vehicle types, prioritizing those with larger profit margins to balance penalties and revenues. For example, small-sized PHEV vehicles would not be initialized in the US emission system. Similarly, the small-sized FCEV project would not start in the Super Credit system



(b) NPV Structure

(a) Fleet Emission

Figure 4: Policy Comparison in Conservative Demand

and would have fewer years in the Dual Credit System and US emission system. The same trend also applies to the small-sized BEV vehicle projects, with fewer projects started after 2029 in the Super Credit System due to a larger demand for other, more profitable low or zero-emission vehicle projects that work to balance the CO_2 emissions. Comparing the three policies, the Dual Credit policy is much less sensitive to the demand scenario for vehicle project initialization because of its credit system policy. The initialized vehicle projects in the optimal project portfolios for the innovate demand are similar to the projects for the conservative demand since there is no threshold but monetary incentives for manufacturers. For the Super Credit System and US Emission System, producers choose the vehicle type with the lowest emissions and the highest profit margin to balance the extra emissions from ICEV types and avoid penalty costs. Once the threshold is met, there is no incentive for manufacturers to produce additional low-emission vehicles. However, for the Dual Credit System, it is always profitable to produce more low-emission vehicles because manufacturers can earn more money for the extra credits earned.

The production quantity graph in Figure 5 also shows a similar trend. In the Dual Credit System, the total production quantity of FCEV and BEV vehicles consistently increases as the production of ICEV types decreases. However, for the Super Credit System and US Emission System, the total production quantity is lower due to reduced demand for ICEV types of vehicles. Additionally, in the innovative demand scenario, the composition of production quantities for different powertrain types does not change significantly. However, in the Dual Credit Policy scenario, the production quantity of zero-emission vehicles increases to earn more money through credits.

Fleet Emission and NPV Analysis

In the Innovative demand scenario, the line plot and bar plot were used to analyze fleet emissions and NPV values, as shown in Figure 6. The black line represents the baseline model with no emission policy. After 2031, due to increased market demand for low emission vehicles, fleet emissions naturally fall below the EU regulated threshold. For the Dual Credit Policy system (yellow line), fleet emissions are much lower, reaching their lowest point after 2032. In the Super Credit System (blue line), emissions follow the EU regulated threshold until 2031, after which they drop further due to market demand. The US Emission System (green line) shows a similar trend, but after 2032, the emission threshold is lower than the EU regulated threshold.

In the NPV structure graph, it can be observed that in the Innovative demand scenario, compared with the conservative demand situation, the differences in objective values between different policies are smaller. The Dual Credit Policy has a higher NPV value, about 4% more compared to the baseline model, due to the extra credits earned. For the Super Credit Policy and US Credit Policy, the objective function values are similar, both about 6% lower. The major reduction occurs before 2031, as after this year, the market itself becomes more favorable toward low emission vehicles, and the regulations have less or no effect on restricting manufacturers from producing more low emission vehicle types.

6.2. Sensitivity Analysis

In the context of sensitivity analysis for the policy factors, this paper selects up to three key factors for each emission policy. These factors are chosen based on their presumed significance on the policy outcomes and their potential for being readily adjusted by governmental authorities. For each factor analyzed, this study employs stacked bar charts to compare the Net Present Value (NPV) structure and the production quantities of different vehicle types. Additionally, it includes objective values and the percentage of low emission vehicles in the total production as represented in the line on the bar chart. The parameters are categorized into three levels with

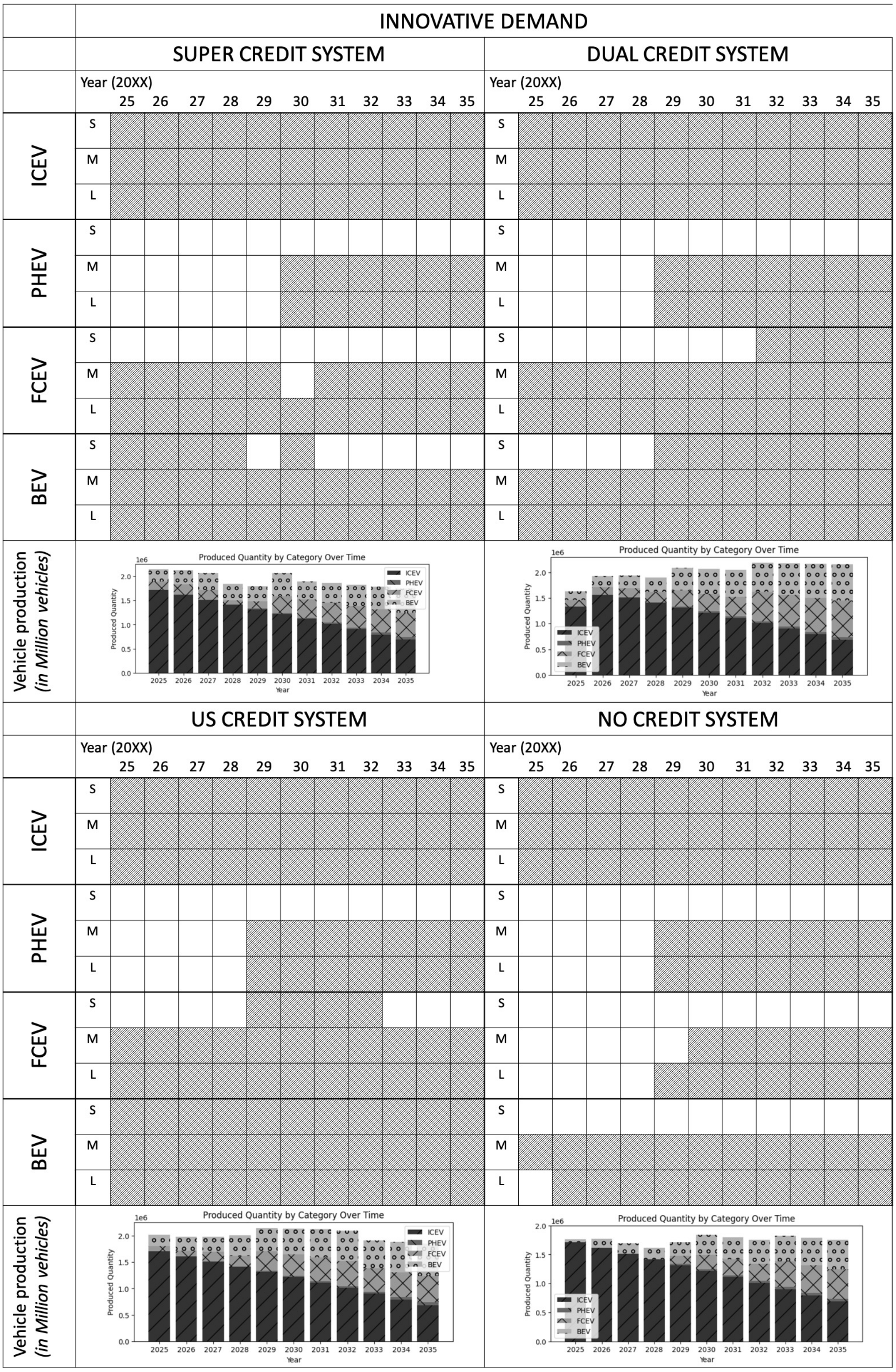
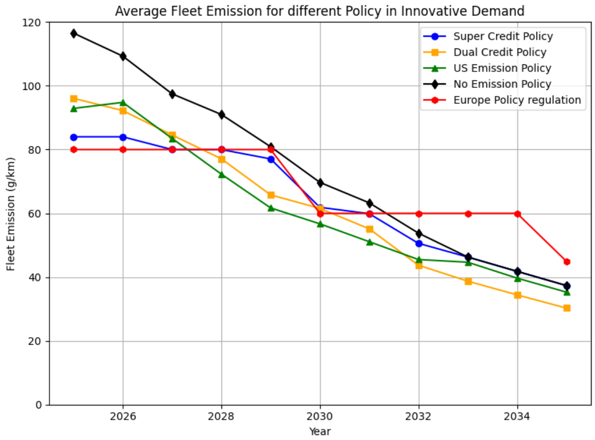
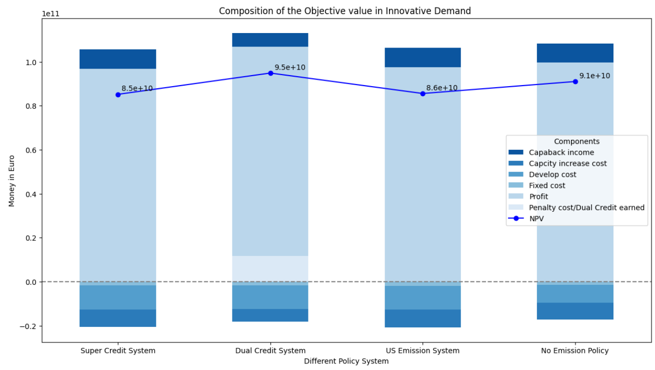


Figure 5: Optimal Portfolio for Different Policy in Innovative Demand

same intervals: high, basic, and low. The rationale behind this categorization is twofold: first, to reduce the experimentation process time, as each instance typically takes around five minutes to yield results, and second, the factors would not influence the trends. Further details regarding the parameter adjustment range can be found in Section 5.3.



(a) Fleet Emission



(b) NPV Structure

Figure 6: Policy Comparison in Innovative Demand

6.2.1. Super Credit System

Under the Super Credit System, this analysis focuses on three crucial factors: the regulated percentage of low emission vehicles, the maximum allowable relaxation percentage, and the PHEV multiplier. The regulated low emission vehicle percentage represents the minimum proportion of low emission vehicles (those emitting less than 50 g/km of CO2) that must be met before relaxation of the emission threshold is permitted. The maximum allowed relaxation percentage sets the upper limit for threshold relaxation. Finally, the PHEV multiplier determines whether PHEV-type vehicles receive a multiplier effect, meaning that when their CO2 emissions reach 50 g/km, they are counted as approximately 0.3 of a production unit instead of 0. The mathematical formulation for these factors can be found in equations 19.

Regulated EV Percentage

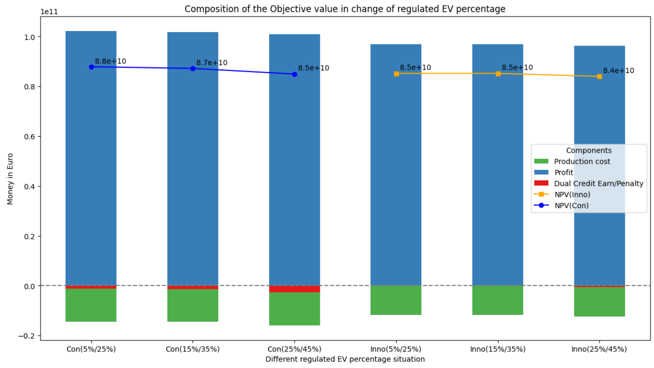
In the objective value diagram, I observe that as the required Regulated Low Emission Vehicle Percentage increases, the objective value is slightly affected, resulting in a decrease in the final NPV value. This trend is similar for both conservative and innovative demand scenarios, as shown in the Objective Value graph in Figure 7. However, the differences are smaller in the innovative demand scenario. The primary factor driving this cost difference is the penalty cost. As the required percentage increases, it becomes more challenging for manufacturers to achieve the goal percentage needed to benefit from the Super Credit Policy. This results in a higher penalty cost, which negatively impacts the NPV value.

In the production portfolio for different vehicle types, I observe a significant difference in the percentage of low emission vehicles produced as the threshold percentage is adjusted. When the threshold percentage is increased by about 10%, the percentage of low emission vehicles produced increases from 32.3% to 34.2%, representing a 2% increase. This change is mainly driven by the increase in the production volume of PHEV vehicles. On the other hand, when the threshold percentage is decreased, there is a slight reduction in the production of low emission vehicles, but this reduction is only about 0.4%, which is relatively small compared to the impact of increasing the threshold. Furthermore, in the innovative demand scenario, the production portfolio shows less variation and remains at a level of about 40%. This percentage level is higher than the percentage assumed for the conservative demand scenario and indicates that in the innovative demand scenario, a larger proportion of low emission vehicles is produced regardless of the threshold percentage.

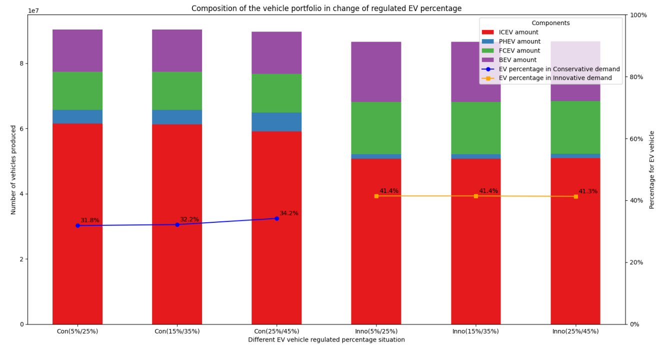
Maximum Allowed Relaxed Threshold

When I analyze the change in the maximum relaxed threshold allowed in the Super Credit System, I observe that as the allowed percentage increases, the objective value also increases. The primary difference is most noticeable in the penalty costs. This trend is more evident in the conservative demand scenario, as in the innovative demand scenario, manufacturers have a stronger incentive to produce low emission vehicles. In conclusion, the relaxation of Super Credit thresholds has a smaller impact on the production portfolio in the innovative demand scenario.

When examining the percentage of low emission vehicles produced in both innovative and conservative demand scenarios, I observe a stable trend with some slight differences. At allowed percentages of about 1% and 9%, the percentages are similar, likely due to changes in PHEV production. However, at higher or lower allowed percentages, manufacturers tend to produce more PHEV vehicles to increase their profits in conservative demand scenarios, while they produce fewer PHEV vehicles in innovative demand scenarios. The percentage of low emission vehicles is more stable in innovative demand, with only a 0.2% change compared to about 1% in conservative demand.

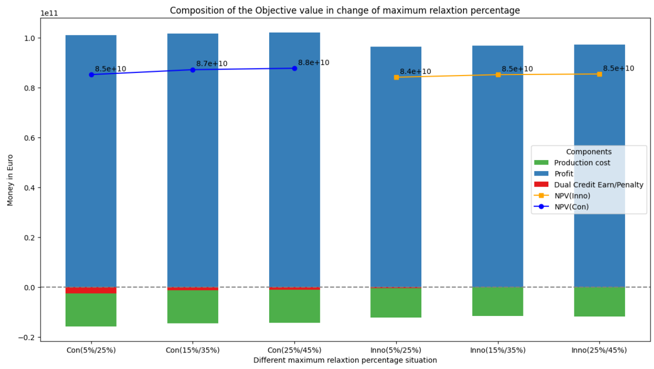


(a) Composition of the Objective Value

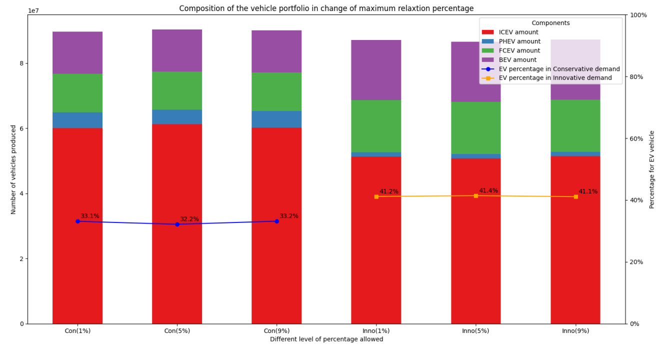


(b) Composition of the Vehicle Portfolio

Figure 7: Analysis for Change of Regulated EV Percentage



(a) Composition of the Objective Value



(b) Composition of the Vehicle Portfolio

Figure 8: Analysis for Change of Maximum Relaxation Percentage

PHEV Multiplier

In the implementation of the super credit policy, the introduction of the PHEV multiplier was intended to incentivize manufacturers to produce more PHEV vehicles. However, the results of the sensitivity analysis suggest that the PHEV multiplier may not significantly influence the behavior of manufacturers, possibly due to the relatively low market demand for PHEV vehicle types. The analysis shows that there are no significant differences in both the NPV graph and the vehicle portfolio graph. The composition and absolute values remain largely unchanged, with the conservative demand scenario consistently having a higher NPV objective value and about 10% fewer low emission vehicles produced.

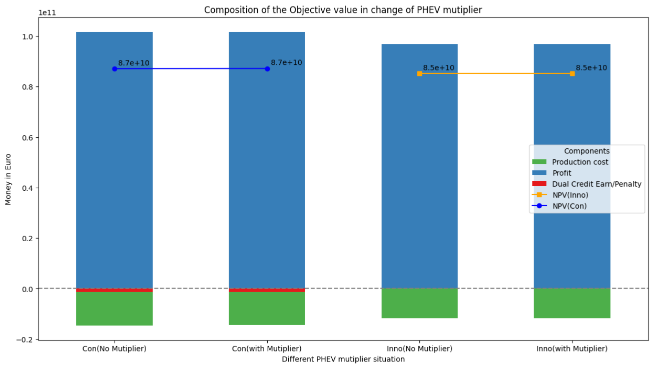
6.2.2. Dual Credit System

In the Dual Credit System, calculating dual credits involves complexity, and this paper simplifies certain factors by using average values. The system comprises three main parts, with one crucial factor selected from each part. These parts encompass the standard fuel consumption in calculating the CAFC score for traditional ICEVs, the credit exchange price, and the NEV weight factor in calculating the NEV score for low-emission vehicles (PHEV, FCEV, BEV). To analyze the impact of these factors, adjustments of approximately 50% compared to the current assumptions were made.

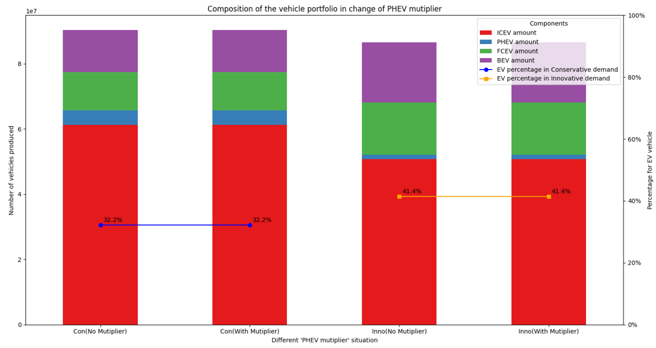
Standard Fuel Consumption (CAFC)

The change in the standard fuel consumption criteria has a notable impact on the manufacturer's objective value. With stricter restrictions, the objective value decreases because the manufacturer's ability to earn dual credits as extra profit diminishes. Conversely, as the standard fuel consumption index becomes more relaxed, the objective value increases. Specifically, a 50% decrease in the index leads to a 27% decrease in the objective value in a conservative demand scenario and an 18% decrease in an innovative demand scenario. Conversely, when the index becomes more relaxed, the objective value increases by approximately 16% in both demand scenarios.

Regarding the percentage of different vehicle types produced, in a conservative demand scenario, a stricter Standard Fuel Consumption index leads to a significant increase in the percentage of low emission vehicles produced, approximately 6%. Conversely, a more relaxed index results in a minor decrease in the percentage of low emission vehicles produced, about 0.4%. In an innovative demand scenario,

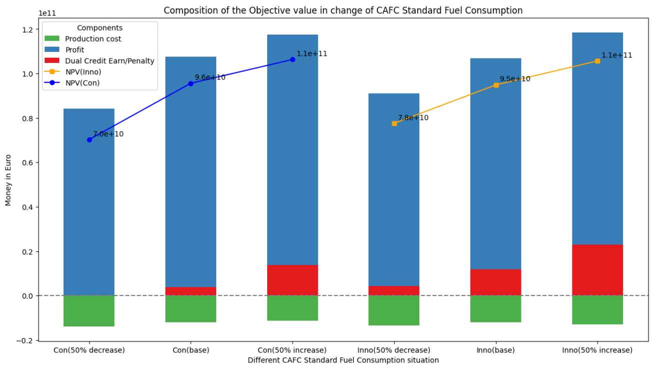


(a) Composition of the Objective Value

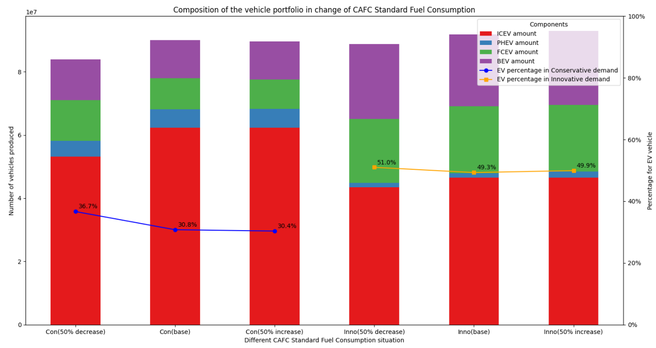


(b) Composition of the Vehicle Portfolio

Figure 9: Analysis for Change of PHEV Mutiplier



(a) Composition of the Objective Value



(b) Composition of the Vehicle Portfolio

Figure 10: Analysis for Change of CAFC Standard Fuel Consumption

a stricter index leads to a smaller increase of around 1% in the production of low emission vehicles, compared to a conservative demand scenario. A more relaxed index in the innovative demand scenario also results in a modest increase of approximately 0.6% in the percentage of low emission vehicles produced, along with an increase in total production volume to earn more dual credit.

Exchange Price

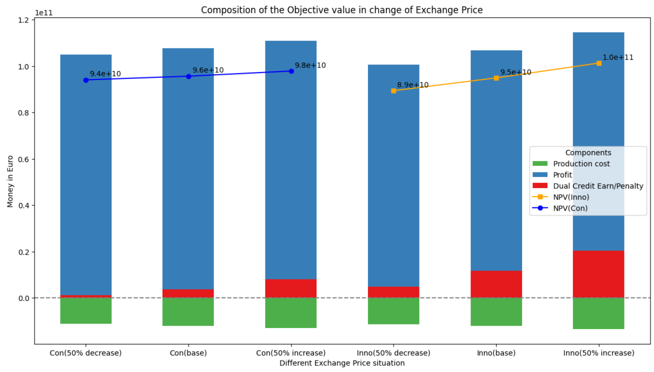
The change in the exchange price for the dual credit policy affects both the objective value and the production portfolio. When the exchange price increases, the objective value for the manufacturer also increases, but the extent of the increase is smaller compared to changes in the Standard Fuel Consumption index in CAFC credit calculation. This trend and value of increment are similar in both conservative and innovative demand scenarios, with about a 50% increase in the price resulting in about a 2% to 5% increase in NPV.

Regarding the production portfolio, as the price increases, manufacturers tend to produce more low emission vehicles to earn the dual credit value. The demand scenario does not significantly affect the trend, and the percentage increase tends to follow a logarithmic pattern rather than a linear one. With a larger price, there is a lower increase rate in the production of low emission vehicles.

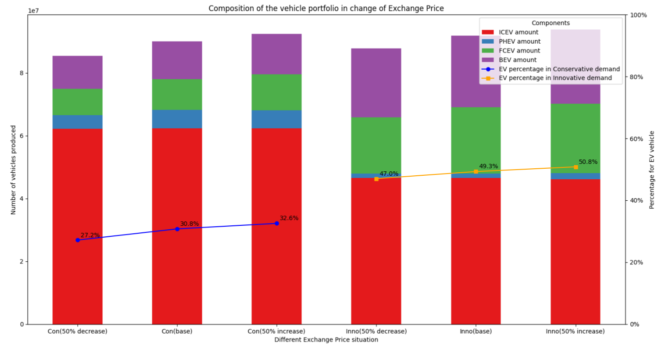
NEV Weighted Factor (NEV)

The NEV weight factor index is a critical factor in determining the NEV score in the dual credit policy system. This factor determines how much low emission vehicles are counted in calculating the NEV score. A higher NEV weight factor index score gives low emission vehicles a higher score in the NEV score calculation, which can help manufacturers earn more value. As the NEV weight factor index increases, the objective value also increases. This trend is consistent in both demand scenarios and increases linearly by about 4.

Regarding the percentage of the production portfolio, an increase in the NEV weight factor index motivates vehicle manufacturers to produce more low emission vehicles in both demand scenarios. The increase is also linear, with a slightly lower rate of increase in the innovative demand scenario, but it results in about a 1% increase in the absolute value in both scenarios. The increase in low emission vehicle production is more prominent for FCEV vehicles since FCEV has the highest NEV weight factor compared to other vehicle types.

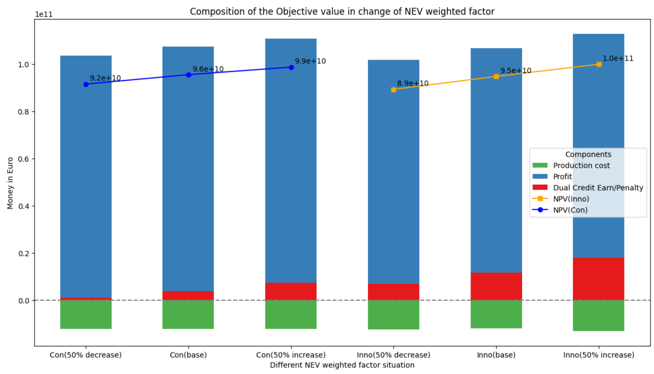


(a) Composition of the Objective Value

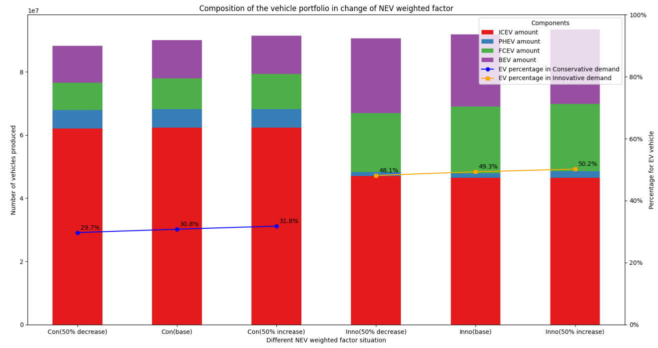


(b) Composition of the Vehicle Portfolio

Figure 11: Analysis for Change of Exchange Price



(a) Composition of the Objective Value



(b) Composition of the Vehicle Portfolio

Figure 12: Analysis for Change of NEV Weighted Factor

6.2.3. US Credit System

The US Credit System is a less complicated emission policy system that only includes a threshold for the average fleet emission volume in each year. However, this threshold is crucial in determining the effectiveness of this policy. A sensitivity analysis is performed on this threshold value to understand its impact on the policy's outcomes.

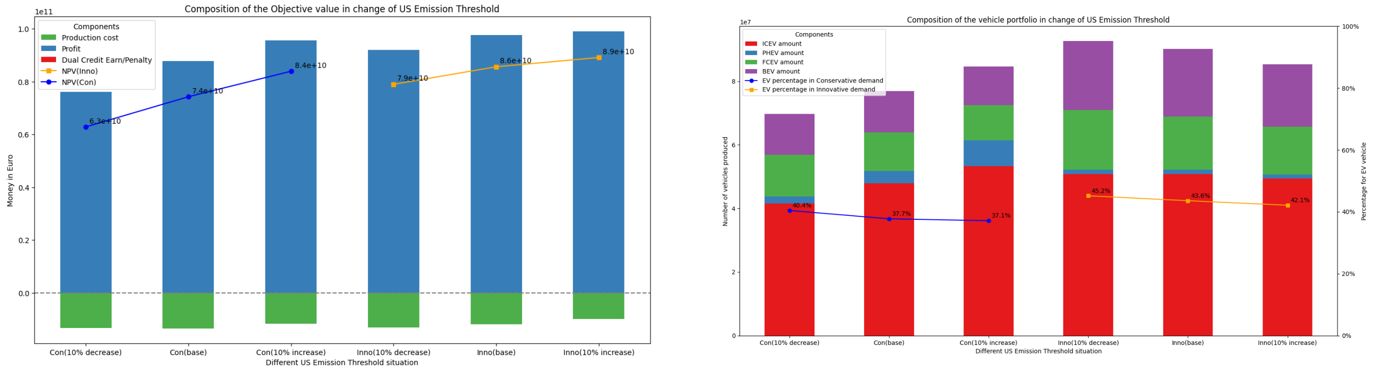
Average Fleet Emission Threshold

Figure 13 shows that the threshold for the average fleet emission has an impact on the objective value as well as the vehicle production portfolio. As the threshold decreases and becomes more stringent, the objective value decreases, with a larger decrease in the conservative demand scenario (about 14%) due to more restrictions on the production of ICEV vehicle types. In the innovative demand scenario, the decrease is about 8%. However, as the threshold is relaxed, the objective increases, to a greater extent in the conservative demand scenario due to the more relaxed restrictions. In the innovative demand scenario, the net objective value does not increase as much because market demand already motivates manufacturers to produce more low-emission vehicles.

Regarding the vehicle production portfolio, allowing fewer fleet emissions leads manufacturers to produce a larger number of low-emission vehicles, a trend that applies to both conservative and innovative demand scenarios. It is also observed that in the conservative demand scenario, a more relaxed threshold encourages manufacturers to produce more ICEV and PHEV vehicles, resulting in a slower decrease in the total percentage of production for low-emission vehicles.

6.3. Factors Analysis

Factorial analysis was conducted to assess how different factors affect the final outcome of the policy. The results were analyzed with a focus on two key indicators: NPV value and EV percentage (the percentage of low-emission vehicle production). These indicators were chosen to evaluate how the factors impact both the manufacturer's profit and the government's environmental goals. The NPV value serves as a measure of how these factors affect the manufacturer's profitability. A higher NPV value is generally preferred by manufacturers, and the government also aims to ensure that manufacturers remain profitable to retain their presence in the country. The EV percentage is used to assess how well manufacturers comply with regulations related to producing environmentally friendly vehicles. A higher EV percentage indicates



(a) Composition of the Objective Value

(b) Composition of the Vehicle Portfolio

Figure 13: Analysis for Change of US Emission Threshold

that a greater number of low-emission vehicles are being produced, which contributes to lower overall CO2 fleet emissions. This aligns with the goals of emission policies to reduce environmental impact. By analyzing how these factors influence NPV and EV percentage, the car manufacturer can better understand the implications of different policy choices on both economic and environmental outcomes.

Three graphs have been generated to analyze the factors. The first one is a Pareto Chart, which is used to assess the absolute value of the importance for each factor and their cross-combinations. The factors are ordered from the most important to the least important, and a red vertical reference line is drawn to indicate which factor is statistically significant. The second plot is the Main Effect Plot, which checks how each factor affects the objective value output. Each factor is represented by a line with a different slope. A horizontal line indicates that the factor has no significant impact on the mean value of the chosen indicator. This allows for the visual analysis of the linear relationship between the factor and the indicator. The last graph is the Interaction Plot, which shows the relationships between different factors and the continuous indicator values. It is plotted in several blocks according to the factors' combinations. The main blocks to be analyzed are the three plots with a white background. By using this interaction plot, the effects of different factors can be compared under two different demand levels, which are considered uncertain factors that need to be estimated. Understanding the differences between different demand levels is essential for the car manufacturer to understand the policy effect. These three plots provide a thorough understanding of these factors and offer insights into the emission policy's details and outlook.

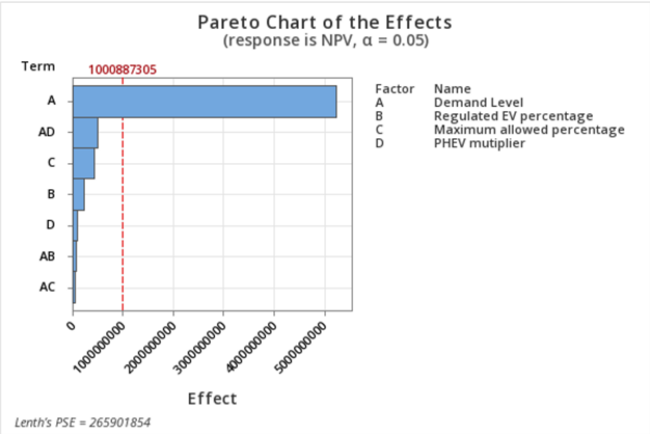
6.3.1. Super Credit System

In the Super Credit System, four factors have been selected, which are the same factors that were analyzed in the sensitivity analysis in section 6.2.1.

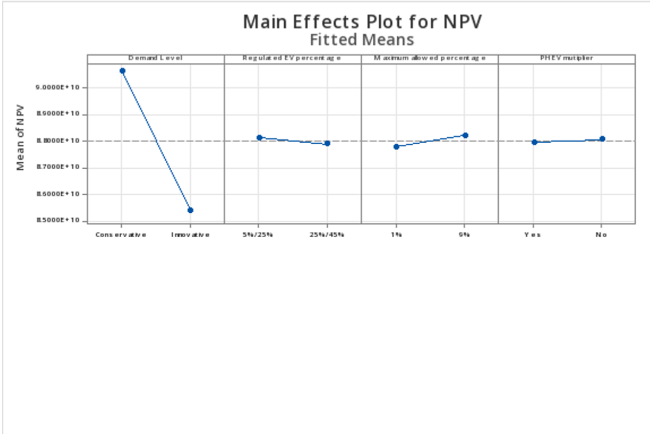
Net Present Value

Figure 14 and Figure 15 contain information related to the factorial analysis of the net present value (NPV) in the Super Credit policy. The Pareto graph in Figure 14 reveals that the demand level has the most significant impact on the net objective value of the vehicle manufacturer, with high statistical significance at the 0.05 level. For the other factors, namely Maximum percentage allowed, regulated EV percentage required, and the PHEV multiplier, their importance is not significantly different and lacks statistical significance at the current confidence level. Additionally, from the main effect chart in Figure 14, it is evident that under the Super Credit policy system, the objective value substantially increases with a conservative demand level, exhibiting a steep slope. Conversely, for the other three factors, the slope is nearly horizontal, indicating minimal differences between lower and higher levels. Lower regulated EV percentage thresholds result in slightly higher profits, while the trend for the maximum percentage allowed differs, resulting in lower objective values for lower percentages. The factor PHEV multiplier does not affect the objective value significantly and remains flat in the fitted means value comparison.

The interaction plot in Figure 15 reveals the interactive relationship between the factors. It is evident that, under different scenarios, the impact of the three factors related to the super credit system remains consistent. The slope lines for low and high values overlap, indicating that conservative demand consistently results in a higher objective value, regardless of variations in the factors. However, as the demand level changes, the effects of factor adjustments show some slight differences. Concerning the regulated EV percentage threshold, in the innovative demand scenario, there is a slightly more noticeable decrease in the objective level as the threshold percentage increases. The maximum percentage allowed does not exhibit differences between different demand scenarios. Yet, for the PHEV multiplier, the trend varies between the two demand scenarios. There is a positive relationship in the conservative demand scenario and a negative relationship in the innovative demand scenario. This suggests that



(a) Pareto Chart for Factor Analysis



(b) Main Effect Plot

Figure 14: Factor analysis in Super Credit System for NPV

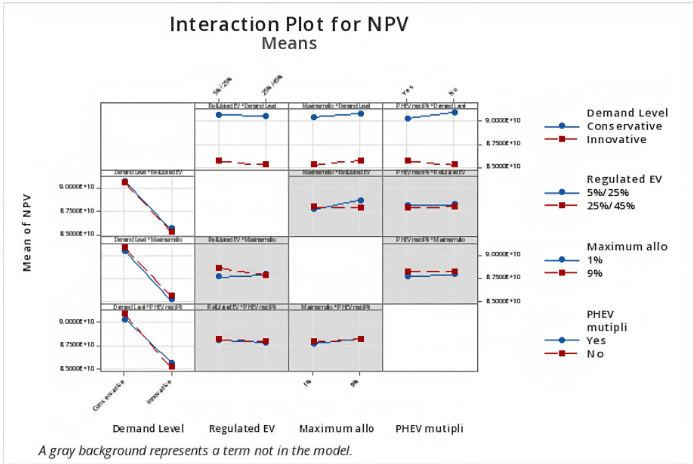


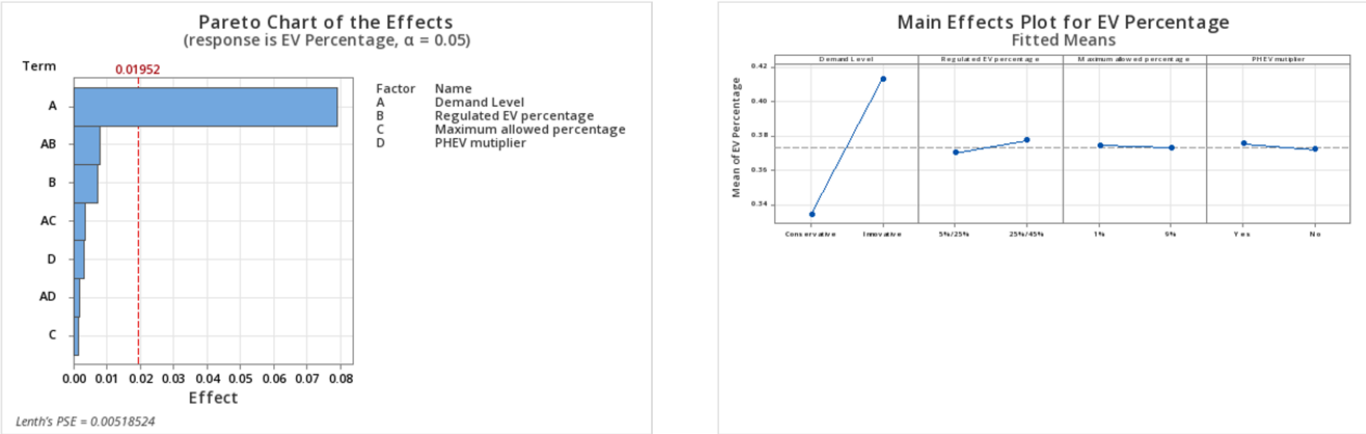
Figure 15: Interaction Plot of NPV in Super Credit System

the implementation of the PHEV multiplier would increase manufacturer profits in a conservative demand scenario but decrease profits in an innovative demand scenario. Although the slope remains flat in this experiment, it could increase as the policy maker assigns a higher value to the PHEV multiplier.

EV Percentage

Figure 16 and Figure 17 provide information regarding the factorial analysis for the percentage of low emission vehicles produced under the Super credit policy. The Pareto chart in Figure 16 indicates that the demand level is the only factor with statistical significance in altering the percentage of low emission vehicles (EVs) produced. The other factors are of similar importance. The main effect plot also illustrates that innovative demand results in a significantly higher percentage of electric vehicle production, represented by a steep slope. Conversely, for the other factors, such as the regulated EV percentage threshold, there is a slight increase in the production volume of electric vehicles. The maximum allowed percentage and PHEV multiplier yield horizontal lines, signifying no substantial differences in the level of electric vehicle production.

Furthermore, the interaction plot in Figure 17 suggests that the policy factor levels do not significantly affect the percentage of electric vehicles produced under different demand scenarios. Only the regulated EV percentage threshold exhibits a flatter slope in the innovative demand scenario, indicating that a lower regulated EV percentage threshold in conjunction with innovative demand results in slightly more electric vehicle production. Regarding the influence of the demand level on the policy factors, there are some minor differences. In the innovative demand scenario, changes in the three Super credit policy factors do not affect the percentage of electric vehicles produced, resulting in a horizontal line. However, in the conservative demand scenario, an increase in the regulated EV percentage threshold leads to higher electric vehicle production, while an increase in the maximum percentage allowed for relaxation and the implementation of



(a) Pareto Chart for Factor Analysis

(b) Main Effect Plot

Figure 16: Factor analysis in Super Credit System for EV percentage

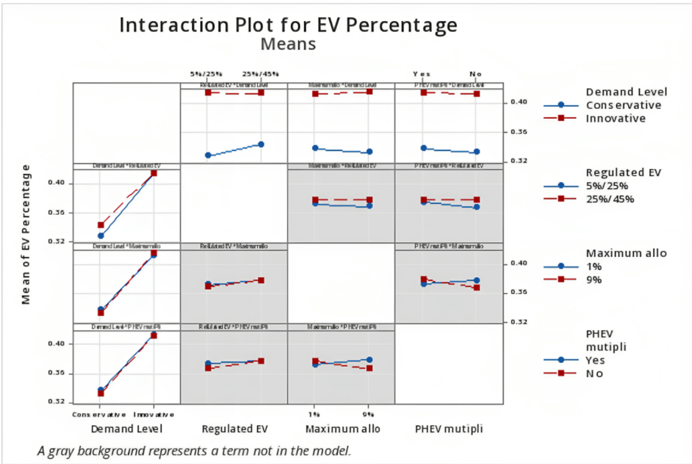


Figure 17: Interaction Plot of EV Percentage in Super Credit System

the PHEV multiplier results in a slight decrease in the percentage of electric vehicles produced. Nonetheless, the decrease in production volume in the latter cases is not significant at the current difference levels.

6.3.2. Dual Credit System

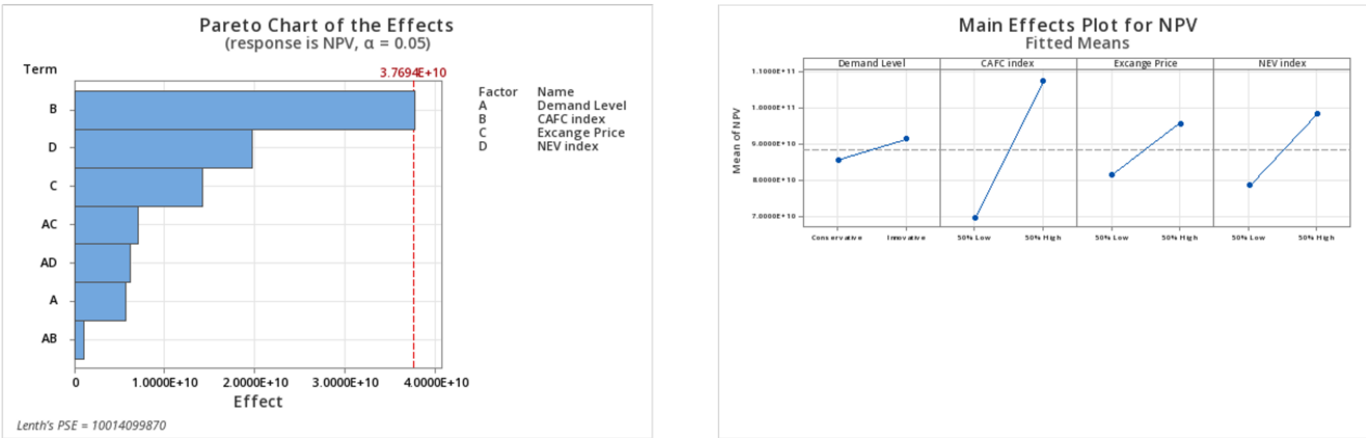
Under the dual credit system, four factors have been selected for analysis, and these factors align with those examined in the previous sensitivity analysis in Section 6.2.2.

Net Present Value

Figure 18 and Figure 19 provide information regarding the factorial analysis of the Net Present Value (NPV) under the Dual Credit policy. From the Pareto chart, it is evident that the most important factor affecting the manufacturer's NPV is the change in the CAFC index, which represents the standard fuel consumption value. This factor is statistically significant at a 95% confidence interval. The following factors, in descending order of importance, are the NEV index (NEV weighted factor), exchange price, and demand level. In the main effect plot, it can be observed that for the demand level and all three dual credit policy factors, there is a linear positive trend. As these factor values increase, the NPV also increases. However, unlike the Super Credit policy, the demand level exhibits only a minor difference, with innovative demand resulting in slightly higher NPV compared to conservative demand.

The interaction plot in Figure 19 is slightly more complex when compared to the Super Credit policy. It reveals the interplay between different factors at different levels and under varying demand scenarios.

For the CAFC index, it is evident that the demand level doesn't have a significant impact on the NPV value. Higher CAFC index values result in higher NPV values, regardless of the demand level. In the case of the exchange price and NEV index, the trend differs between the two demand scenarios. When the exchange price is high, both demand scenarios yield similar NPV values. However, as the exchange price decreases to a lower value, the innovative demand scenario leads to higher earnings for the manufacturer. Regarding



(a) Pareto Chart for Factor Analysis

(b) Main Effect Plot

Figure 18: Factor analysis in Dual Credit System for NPV

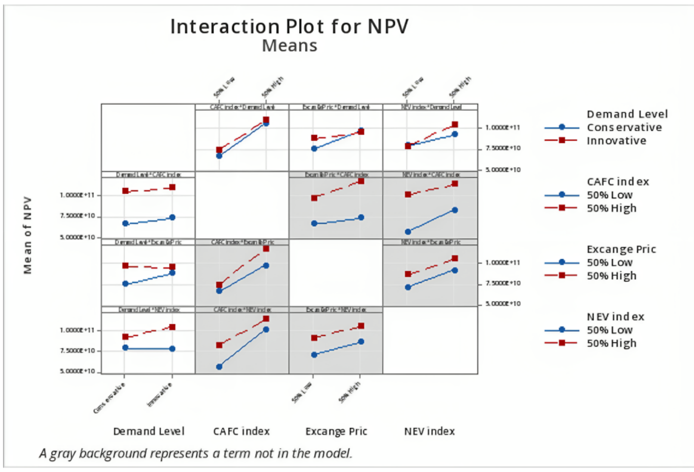


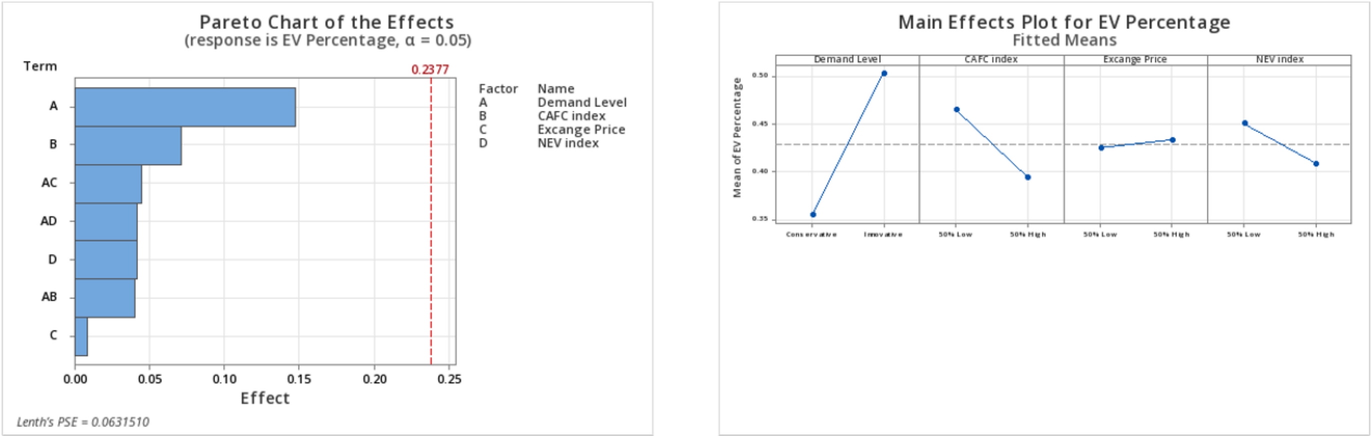
Figure 19: Interaction Plot of NPV in Dual Credit System

the NEV index, the trend is opposite to that of the exchange price. In the innovative demand scenario, a higher NEV index results in greater earnings. As the NEV index decreases to lower levels, the benefits diminish. The full matrix interaction plot also demonstrates the effects of changing policy factors under different demand levels. In a conservative demand scenario, the CAFC index exhibits the steepest positive slope, followed by the exchange price and NEV index, which have similar positive slopes. This suggests that increasing these factor values leads to higher earnings for the manufacturer. Conversely, in the innovative demand scenario, the CAFC index doesn't result in significant differences. However, the slope for the exchange price becomes flatter, indicating a lower increase in NPV value as the exchange price increases. The NEV index slope becomes steeper, signifying higher profits as the NEV index value increases.

EV Percentage

Figure 20 and Figure 21 provide information on the factorial analysis for the percentage of low emission vehicles produced under the Dual credit policy. The Pareto Chart reveals that none of the factors have statistical significance in affecting the percentage of electric vehicles produced in the Dual emission policy system. The demand level is the factor with the most significant impact, but it does not reach statistical significance. From the main effect plot, it can be concluded that the innovative demand scenario results in a higher percentage of electric vehicle production. The CAFC index and the NEV index reduce the proportion of electric vehicles produced, with higher index values indicating greater tolerance for fuel-powered vehicles. However, the exchange price does not significantly affect the percentage of electric vehicles produced, as there is no observable difference as the price changes from low to high.

The interaction plot in Figure 21 shows that the values of the dual policy factors do not alter the trend of electric vehicle production in different demand levels. Innovative demand consistently leads to a higher percentage of electric vehicles in the production portfolio. The slope varies, with



(a) Pareto Chart for Factor Analysis

(b) Main Effect Plot

Figure 20: Factor Analysis in Dual Credit System for EV percentage

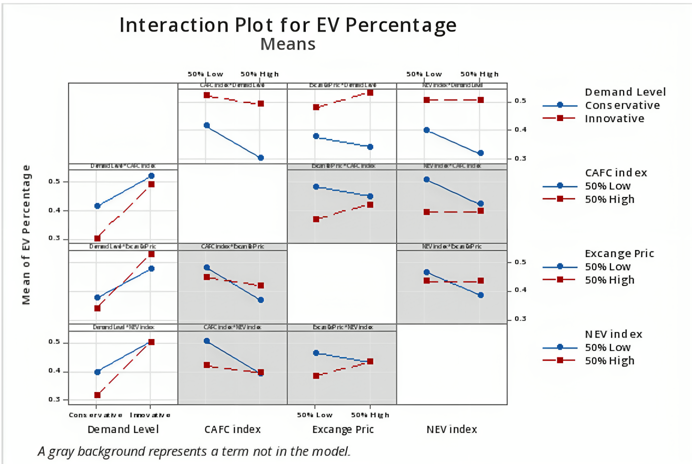
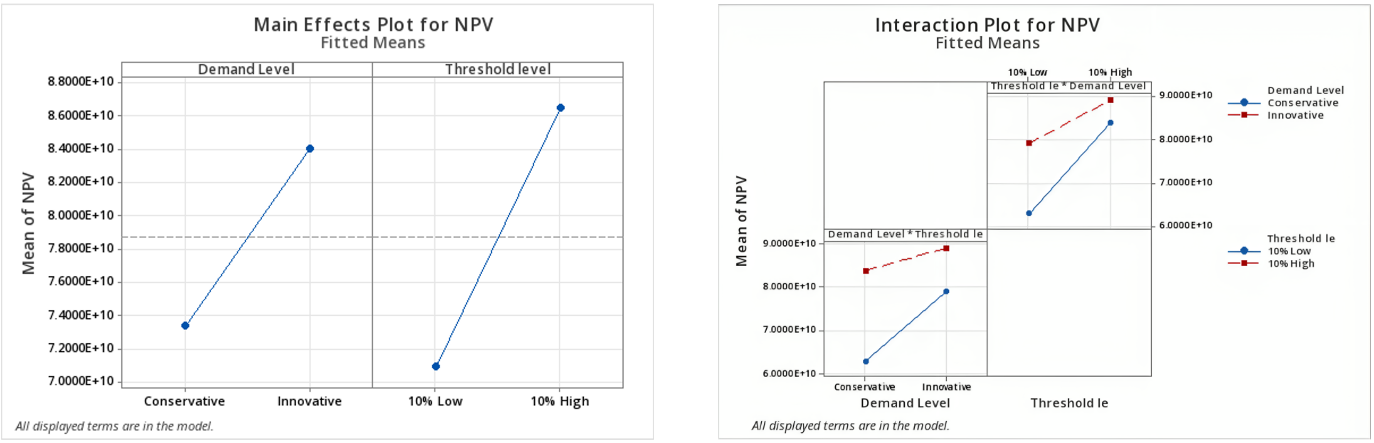


Figure 21: Interaction Plot of EV Percentage in Dual Credit System

higher values of the three dual policy factors resulting in a greater increase in the percentage of electric vehicles in the production portfolio. Regarding the influence of changes in dual credit policy under different demand levels, in a conservative demand scenario, the percentage of electric vehicle production decreases as the factor values increase. The CAFC index exhibits the largest slope, followed by the NEV index and the exchange price. However, in the innovative demand scenario, the impact of changes in the CAFC index and NEV index is much lower, and for the exchange price, the percentage of electric vehicle production actually increases as the price increases. This may be due to increased market demand for low-emission vehicles, motivating manufacturers to produce more electric vehicles to earn from the dual credit score and achieve better profits.

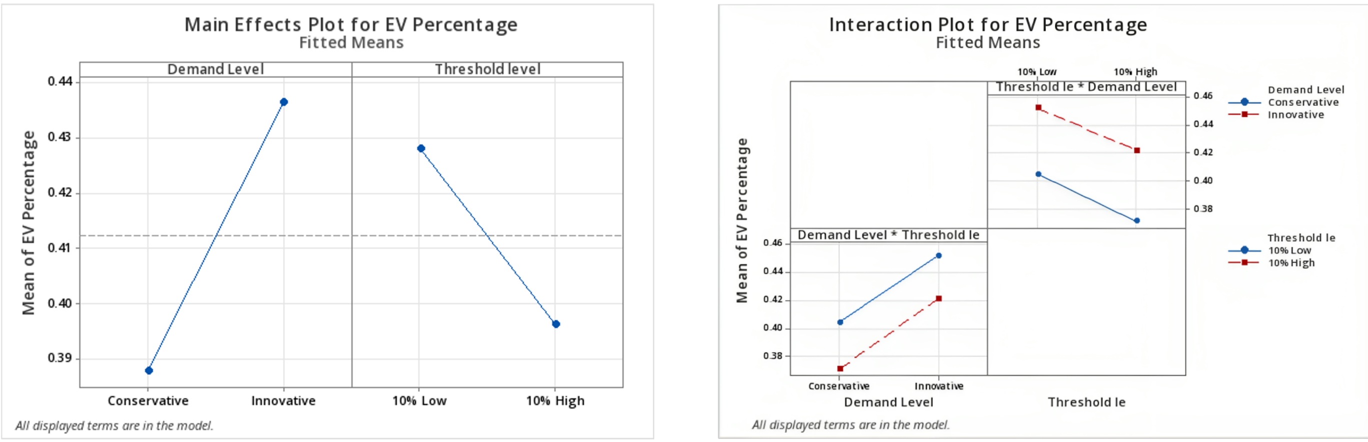
6.3.3. US Credit System

The US credit system is simpler, with only one policy-related factor, which is the CO_2 emission threshold value. Figure 22 and Figure 23 depict the main effect and interaction plots for the net present value (NPV) and the electric vehicle (EV) percentage in the entire production portfolio. For the net present value, in the innovative demand scenario and with a higher level of the emission threshold, the manufacturer achieves a higher NPV. The slope is similar, indicating that the difference in threshold value has a consistent effect on the NPV regardless of the demand level. The interaction plot shows that in the conservative demand case, the NPV is more sensitive to changes in the threshold value, but the innovative demand scenario consistently results in a higher NPV. Regarding the electric vehicle percentage in the production portfolio, the innovative demand scenario yields a higher electric vehicle percentage. However, a higher threshold value leads to a lower proportion of electric vehicles produced. The effect of threshold changes on the electric vehicle production percentage is consistent in both demand scenarios, with innovative demand consistently resulting in a higher percentage of electric vehicles produced, albeit with some absolute value differences.



(a) Main Effect Plot (b) Interaction Plot

Figure 22: Factor analysis in US Credit System for NPV value



(a) Main Effect Plot (b) Interaction Plot

Figure 23: Factor analysis in US Credit System for EV percentage

7. Conclusion and Outlook

This article employs a mathematical model, primarily a mixed-integer linear model, to characterize car manufacturers' production portfolios under different emission policies. The aim is to gain a more quantitative understanding of various policy systems and their effectiveness. By integrating actual datasets with different demand scenarios and policy parameters, the study simulates the impact of these policies, assuming that manufacturers strive to maximize their profits.

The results indicate that all three policy systems in Europe, China, and the United States contribute to increased production of low-emission vehicles compared to the base model with no policy in place. Regarding the initialization of low-emission vehicles, the US emission policy leads to the most significant increase in the number of vehicle initiations, while the Super Credit Policy in Europe and the Dual Credit Policy perform similarly in this regard. However, from a financial perspective, the Dual Credit Policy performs the best in preserving the car manufacturer's profit, while the US emission policy has the most detrimental effect on the manufacturer's profit. For the average fleet emissions, both the Super Credit Policy and the US emission policy effectively track the trend set by the regulated emission threshold. However, the Dual Credit Policy does not have a fixed threshold but rather follows emissions according to market trends. As the market increasingly favors low-emission vehicles, resulting in a shift towards an innovative demand scenario where consumers prefer such vehicles, the fleet emissions are lower in response to this trend.

Furthermore, my experiments show that, it is evident that for the Super Credit Policy and the US Emission Policy, the demand level has a significant impact on the profit of the car manufacturer and the percentage of low-emission vehicles produced. In contrast, the Dual Credit Policy exhibits notable differences, where the demand level appears to influence primarily the percentage of low-emission vehicles produced but not the objective value.

Speak to the specific parameter factors, the Super Credit

System does not exert a substantial influence on either of the indicators, namely NPV (Net Present Value) and EV (Electric Vehicle) percentage. However, for the Dual Credit Policy and the US Emission Policy, these factors exhibit a relatively higher effect on both indicators, with the CAFC index being the most significant factor in the Dual Credit Policy. Notably, the market exchange price for the Dual Credit only appears to impact the net present value and not the percentage of low-emission vehicle production. In the context of the US emission policy, the only factor, which is the carbon fleet emission threshold, plays a significant role in determining the manufacturer's profit and the policy's effectiveness.

There are several limitations to this study. Firstly, regarding the model solving method, the Super Credit System policy is not formulated as a linear model and cannot be readily transformed into a linear form for optimization. Instead, a heuristic method was employed to solve this model in two steps. While this approach may not guarantee an optimal solution, however, my experiments showed that the heuristic gives good quality solutions that resulting deviations are unlikely to have a significant impact.

Secondly, in this study, market demand is based on simplified assumptions and is not specific to individual vehicle models. The total demand amount is assumed to be constant for each year in the planning period, and vehicle sales quantities may vary due to consumer preferences. Additionally, the vehicle type segmentation used in this study is relatively broad, categorizing vehicles based on powertrain technology, size, year, and power range. In reality, there is a much larger variety of vehicle models. To address this limitation, a more accurate demand prediction model could be integrated into the analysis to enhance result accuracy.

Thirdly, some of the policy-specific parameters are based on assumptions. For instance, in the Dual Credit Policy system, certain parameters such as fuel consumption standard in CAFC score calculation or the weighted factor for actual NEV credit calculation are calculated based on detailed descriptions of specific vehicle models and are not included in the dataset due to privacy concerns. Obtaining a more comprehensive dataset may require closer collaboration with vehicle manufacturers.

At last, in the real market scenario, the cooperation between the different vehicle manufacturer should also been considered. In this study, it is assumed that only one vehicle manufacturer exists and there would be any market trading activity occurs. These activities is hard to be modelled but if necessary could be added to this model for a more accurate result.

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