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Summary

The European Union's decarbonisation strategy necessitates profound shifts across all sectors, with road transport pre-senting a particularly formidable challenge due to its sustained emissions growth since 1990. Given that Italy's road transport sector is the third-largest consumer of fossil fuels in Europe, its role is pivotal in achieving these collective climate objectives. This study employs grey forecasting models to assess the projected contribution of alternative fuels - specifically biodiesel, bio-gasoline, biomethane, and electricity - to Italy's 2030 decarbonisation pathway. The results suggest that consumption of these energy carriers will reach around 5 Mtoe (million tons of oil equivalent), representing a threefold increase compared to 2022 levels. While our analysis forecasts that biomethane, will entirely displace its fossil counterpart and that electricity consumption will expand considerably, the progress in the use of liquid biofuels could be lower than that reported in Italy's National Energy and Climate Plan (NECP). According to grey models, in 2030, alternative fuels could meet one-sixth of the final energy demand for Italian road transport: a considerable improvement from current levels but less than the two-fifths share needed to align with the EU's broader decarbonisation objectives. The findings suggest that the decarbonisation of road transport, largely attributed to the use of biofuels, is currently outpacing the progress achieved through the electrification of the vehicle fleet. This un-derscores the imperative of adopting a holistic strategy that leverages the full potential of all technologies. Such a unified design is essential to foster synergy and expedite the achievement of climate objectives in a manner that is both efficient and inclusive.

Keywords: Road Transport, Final Energy Consumption, Alternative Fuels, Italy’s National Energy and Climate Plan, Grey Forecasting Models

JEL Classification: Q2, Q4, C22, C45, C53

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Abstract

The European Union's decarbonisation strategy necessitates profound shifts across all sectors, with road transport presenting a particularly formidable challenge due to its sustained emissions growth since 1990. Given that Italy's road transport sector is the third-largest consumer of fossil fuels in Europe, its role is pivotal in achieving these collective climate objectives. This study employs grey forecasting models to assess the projected contribution of alternative fuels - specifically biodiesel, bio-gasoline, biomethane, and electricity - to Italy's 2030 decarbonisation pathway. The results suggest that consumption of these energy carriers will reach around 5 Mtoe (million tons of oil equivalent), representing a threefold increase compared to 2022 levels. While our analysis forecasts that biomethane, will entirely displace its fossil counterpart and that electricity consumption will expand considerably, the progress in the use of liquid biofuels could be lower than that reported in Italy's National Energy and Climate Plan (NECP). According to grey models, in 2030, alternative fuels could meet one-sixth of the final energy demand for Italian road transport: a considerable improvement from current levels but less than the two-fifths share needed to align with the EU's broader decarbonisation objectives. The findings suggest that the decarbonisation of road transport, largely attributed to the use of biofuels, is currently outpacing the progress achieved through the electrification of the vehicle fleet. This underscores the imperative of adopting a holistic strategy that leverages the full potential of all technologies. Such a unified design is essential to foster synergy and expedite the achievement of climate objectives in a manner that is both efficient and inclusive.

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1. Introduction

The European Union (EU) has pledged to reduce net greenhouse gas (GHG) emissions by 55% from 1990 levels by 2030 and to achieve climate neutrality by 2050. This ambitious decarbonisation pathway demands (and will continue to demand) a radical transformation of numerous sectors, particularly the transport sector, which is required to neutralise over 400 million tonnes of CO_2 in 5 years and more than 700 million in 25 years.

Acknowledging the difficulty of the targets, the resources available, the processes already in place and the need for a common approach, the EU has also indicated the modus operandi: electrification of consumption (for non-hard-to-abate activities). In fact, if the consumption of all economic activities were met by electricity produced from renewable sources, the climate-changing emissions associated with the combustion of fossil fuels would be reduced to zero.

For some sectors, road transport in primis, the adoption of this strategy is proving more complex than expected and decarbonisation is lagging. Thus, even though the EU achieved an almost 30% decrease in net greenhouse gas emissions between 1990 and 2023, certain sectors experienced a rise: +20% in the case of road transport[1].

In the past, the progress of sectors subject to the EU-Emissions Trading Scheme (EU-ETS) has been sufficient to make up for the shortcomings of activities not subject to this mechanism. However, with the tightening of recent targets, it is increasingly difficult to ensure that cross-sector emission offsetting remains consistent with the total emission reduction goals. Meeting future targets requires overcoming inertia and acceleration of the progresses in all sectors in all Member States. According to the latest estimates, the Paris Agreement's target is only achievable if net CO_2 emissions from the transport sector contract by at least 90% over the next 25 years. With over 54 million vehicles on the road by 2023 (of which 4% are brand new), Italy ranks second in the EU for the total number of vehicles and third for final energy consumption from road transport. About 1/7 of the EU's road transport decarbonisation target depends on Italian performance. Determining whether, and to what extent, Italy's road transport consumption has been (and is going to be) neutralised is essential to assessing the feasibility of meeting the EU's targets within the Paris Agreement timeframe. The focus of this work is final energy demand of road transport in Italy by source, that is, the demand of energy carriers by all vehicles circulating on the road: buses, cars, commercial vehicles (light and heavy), quadricycles and motorbikes. This work has three main objectives: firstly, to outline the status quo; secondly, to assess future prospects (by 2030); and, finally, to verify the consistency of the trend with the commitments undersigned (at both EU and country-level).

The analysis of changes in standards and consumption of alternative fuels to conventional ones is a compulsory starting point: it makes it possible to identify available alternatives, quantify progress and understand recent performance[2]. Once the status quo has been clarified, the next step is to estimate future progress: this makes it possible to understand how much of the energy consumption of

[1] We would remark that the rise in transport sector emissions has been significantly lower than the growth in mobility demand during the period under consideration. According to the European Environment Agency (EEA), in road transport, passenger transport demand has increased by over 50% since 1990, while freight transport demand has grown by more than 80%.

[2] In the context of this study, traditional fossil fuels include diesel, gasoline, liquefied petroleum gas (LPG) and natural gas, both compressed (CNG) and liquefied natural gas (LNG).

road transport can reasonably be met by alternatives to traditional fossil fuels in the time horizon of interest. In our case, to 2030. Considering the scope of application and the available data, the choice fell on data-driven estimation methods which, according to the most recent literature (Javed et al., 2020), provide more accurate forecasts than conventional deterministic approaches. Grey forecasting models have been widely applied to forecast energy consumption. However, no prior research has applied these models to the Italian context. Furthermore, existing applications have not estimated the consumption of a wide variety of alternatives to traditional fossil fuels. This study, therefore, fills a significant gap in the literature by providing the first application of grey models to forecast the future energy mix for Italy's road transport sector. This work also offers a novel approach by assessing the combined potential of a range of alternative fuels—including biodiesel, bio-gasoline, biomethane, and electricity—to contribute to a national decarbonization pathway.[3] Having outlined the consumption outlook to 2030, the last step is the comparison with policy targets. Italy's latest National Energy and Climate Plan (NECP) sets forth a very ambitious agenda to increase energy consumption from alternatives to traditional fossil fuels, posing a significant challenge for the road transport sector: by 2030, biodiesel, bio-gasoline, biomethane, and electricity will need to supply more than 6 million tonnes of oil equivalent (Mtoe). This figure is a fourfold increase from 2022 levels and should account for one-fifth of road transport's final energy demand in 2030. Is this path consistent with grey models' estimates? Only partially. Grey models consider achieving 80% of the 2030 NECP target to be a reasonable goal. The remaining 20% of the target is not consistent with current dynamics; its achievement is conditional on the implementation of additional measures[4]. According to grey models, by 2030, all-natural gas consumed by road transport will be of biological origin and, while fossil fuels will continue to dominate, the average share of renewables in diesel and gasoline on the market will increase significantly. In the case of diesel fuel, the average blending at the pump could range from 10% to 15%, depending on trends in overall fuel consumption[5]. Based on 2023 data, the average blending of gasoline at filling stations was around 1%, a level considerably lower than the EU average. Due to this trend, and without accounting for any new policy changes, it appears improbable that the average blending level of gasoline will reach 5% by 2030. Instead, the current trajectory suggests a stabilisation at 2-3%. Nevertheless, the mandatory blending requirements for fuel suppliers introduced in 2023 have the potential to significantly surpass this projected trend. This kind of outcome has already been documented in other EU nations. Moreover, projections indicate that electricity will provide over 1 Mtoe of energy for road transport in 2030. Fulfilling the established targets for renewable electricity generation should ensure that at least 65% of this energy is derived from non-fossil sources.

Although the decarbonisation of road transport consumption is progressing more rapidly than the electrification of vehicle fleets (Bonacina et al, 2024), the replacement of fossil fuels with climate-

[3] In this study, we draw on the literature on grey forecasting models to quantify the consumption, up to 2030, of the main alternative fuels used in Italian road transport: biodiesel, bio-gasoline, biomethane, and electricity. The available data did not allow us to include bio-LPG, e-fuels, and recycled carbon fuels (RCF) in the estimates.

[4] Additional measures include those already in place, the effects of which have not yet been internalised by the data.

[5] A 10% blending means that for every 100 toe (tonnes of oil equivalent) of fuel, 10 toe are of renewable origin, with the remainder being fossil-based.

neutral alternatives will, at best, only facilitate the fulfilment of approximately 40-50% of the existing EU decarbonisation target by 2030[6].

This paper is structured as follows. Section 2 provides an overview of the European and Italian regulatory frameworks that have influenced the integration of alternative fuels in road transport. Section 3 then analyses energy consumption within Italy's road transport sector. The methodological approach is concisely presented in Section 4, with data sources detailed in Section 5. Sections 6 and 7 present the in-sample and out-of-sample results, respectively. A critical comparison of the grey models' forecasts with national and European 2030 goals is provided in Section 8 and Section 9 concludes the paper.

2. The Regulatory Framework

The European Union's regulatory framework concerning low carbon energy carriers is undeniably dynamic and ambitious, reflecting the increasing urgency to address the climate crisis and reduce reliance on fossil fuels. The legislative evolution, from Directive 98/70/EC to the very recent RED III (Renewable Energy Directive III, Directive 2023/2413/EU), demonstrates a clear trajectory towards decarbonisation, yet it is not without complexities, challenges, and critical issues that warrant in-depth analysis.

Directive 98/70/EC (Fuel Quality Directive, FQD), dating back to 1998, marked the inception of the European regulatory journey on fuels, primarily focusing on reducing atmospheric pollution caused by motor vehicles. Although it already encompassed the foreseen use of biofuels to enhance fuel quality and reduce GHG emissions (with a binding target of a 6% reduction by 2020 compared to 2010 for diesel and gasoline on the EU market), its scope was predominantly linked to fuel quality rather than specific blending targets. This initial approach, while fundamental, was reactive to the local pollution emergency rather than proactive regarding the global climate challenge.

The true turning point for renewable fuels came with Directive 2003/30/EC, which introduced the first indicative targets for biofuels. The non-binding nature of these targets represented an initial critical point: despite demonstrating an intent, the absence of compelling obligations limited the actual impact on biofuel adoption in the early years. Italy, in transposing this directive with Legislative Decree 128/2005, followed this line, setting non-binding objectives which, while important for initiating the discussion, did not generate significant acceleration.

Directive 2009/28/EC (RED I) represented the first truly significant and binding step in the EU's commitment to sustainable fuels. The introduction of a 10% target for energy from renewable sources (RES) in the transport sector by 2020 was crucial, as it provided a clear incentive to increase the share of biofuels. Concurrently, the introduction of the first sustainability criteria for biofuels marked an important recognition of the potential environmental issues associated with their production (e.g., deforestation, competition with food and feed crops). This move began to shift the focus from mere quantity to the quality and sustainability of biofuels. Italy's transposition with Legislative Decree 28/2011 reinforced this path, refining the mechanism of Certificates of Immission for Consumption (CIC) and establishing an initial national target for advanced biofuels. This was a positive sign,

[6] The 40% figure is based on the grey estimation results, whereas the 50% figure corresponds to the results reported in the latest Italian NECP.

acknowledging the need to promote biofuels with a lower environmental impact, although the initial share of 0.5% was still modest.

Subsequent Directives, particularly 2015/1513 (ILUC, Indirect Land-Use Change) and 2018/2001 (RED II), continued to refine the framework. A critical aspect of the previous legislation was the (unintentional) incentive for biofuel production from food and feed crops, which could lead to issues of indirect land-use change and competition with food (and feed) production. The ILUC Directive responded to this critical issue by limiting the share of biofuels from food and feed crops that could be counted towards renewable energy targets in transport to 7%, an essential step to mitigate negative impacts. RED II further raised the bar, setting a binding target of 14% for energy from RES in the transport sector by 2030 and introducing more stringent sustainability criteria. This pushed towards biofuels with superior environmental performance, aiming to ensure their genuine contribution to combating climate change. Italy's transposition with Legislative Decree 199/2021 and its integration into NECP 2019 confirmed alignment with European ambitions, with significant estimates for the use of renewable fuels and electricity in road transport by 2030.

Despite these advances, the pace of transport decarbonisation has often been judged too slow relative to climate imperatives. Criticisms have focused on the actual availability of sustainable raw materials for advanced biofuels and the slow large-scale adoption of zero-emission vehicles.

Table 1. Status Quo and NECP Targets without Multipliers in ktoe.

	Sector	*Coeff.*	*Status quo*	*NECP trajectory*	
			2022	2025	2030
Single counting (conventional) bioliquids	Road	1	100	630	980
Advanced bioliquids	Road/Rail	2	1,290	1,780	3,470
Single counting (conventional) biomethane	Road	1	0	0	0
Advanced biomethane	Road/Rail	2	180	470	820
Electricity from RES	Road	4	20	120	610
RFNBO	Road/Rail	2	0	10	360
Final energy consumption	Transport		43,640	42,560	42,470

The most recent regulations, culminating in Directive 2023/2413 (RED III), reflect a clear need for acceleration. The introduction of even more ambitious targets[7] and the emphasis on advanced biofuels and renewable fuels of non-biological origin (RFNBOs) demonstrate a decisive shift. This moves the focus towards solutions with greater decarbonisation potential, such as electrofuels (e-fuels) and second-generation biofuels. Italy's NECP 2024, while awaiting the formal transposition of RED III (to be completed by May 2025, sic!), already internalises this need for acceleration. Estimates of a tenfold increase in traditional sustainable biofuels, a threefold increase in advanced biofuels, and the introduction of significant RFNBO consumption show a clear intention to tackle the challenge. Table 1, which quantifies these targets[8], highlights the scale of these commitments. The feasibility of these objectives, especially for electrofuels and electricity from RES in road transport, will critically depend on production capacity, availability of charging and refuelling infrastructure, and the diffusion of e-vehicles. The figure for electric cars circulating in Italy at the end of 2024 (fewer than 400,000

[7] 29% of RES in final energy consumption across all transport modes or a reduction of at least 14.5% in GHG intensity in the fuels used within the sector by 2030.

[8] For example, nearly one million tonnes of oil equivalent of traditional biodiesel and bio-gasoline and over 3.4 Mtoe of advanced biodiesel and bio-gasoline by 2030.

units compared to the 6.6 million estimated for 2030 in NECP 2024) underscores the vast disparity and the challenge facing Italy.

It is also crucial to mention the EU regulations on tailpipe emissions (gCO_2/km) for new passenger cars and commercial vehicles. These include Regulations (EU) 2019/631, 2019/1242, 2023/851, and 2024/1610. These regulations have effectively incentivised the production of electric vehicles (battery or fuel cell) and plug-in hybrids, at the expense of traditional internal combustion engine vehicles. Such regulations, by influencing changes in the vehicle fleet, can impact the energy mix employed by circulating vehicles.

The EU regulatory framework on sustainable fuels has evolved from an approach focused on air quality to an increasingly stringent commitment to decarbonisation. The progression from indicative targets to binding objectives, coupled with the introduction of increasingly stringent sustainability criteria, the limitation of biofuels derived from agri-food crops, and the impetus towards advanced biofuels and RFNBOs, collectively signify a mature and ambitious strategic evolution. The main critical issues and challenges for the future include:

- Scale of Production: the capacity to produce advanced biofuels and RFNBOs in sufficient quantities to meet the new targets remains a significant unknown. It requires massive investment in research, development, and production infrastructure;
- Policy Harmonisation: ensuring that fuel policies and vehicle policies operate in synergy is essential to avoid inconsistencies and maximise the effectiveness of decarbonisation;
- Costs: advanced sustainable fuels and RFNBOs are currently more expensive than fossil fuels. Effective support mechanisms and incentives will be necessary to overcome this economic barrier and make them competitive;
- Infrastructure: the widespread adoption of electric and hydrogen vehicles requires robust and widespread charging and refuelling infrastructure, the realisation of which is still underway and presents significant challenges.
- Social Acceptance: the transition will also require acceptance and adaptation from consumers and industry.

Ultimately, EU legislation is laying the groundwork for a profound transformation of the transport sector. Success will depend not only on the clarity and ambition of the directives but also on the capacity of Member States (Italy included) to translate these objectives into actions, investments, and large-scale innovations.

3. Changes in Road Transport Consumption and Determining Factors in Italy (1990-2023)

From 1990 to 2023, Italy's road transport experienced significant shifts in final energy consumption and its underlying drivers, driven by evolving policy frameworks and underlying socioeconomic factors. In 1990, the movement of approximately 33 million vehicles necessitated 31 Mtoe of energy, exclusively supplied by fossil fuels such as diesel, gasoline, LPG and natural gas[9]. Whilst vehicle fleet size and energy consumption initially grew in parallel until the early 2000, this relationship subsequently decoupled. Energy consumption began to decelerate and contract, even as the demand for mobility (driven by rising incomes and increasing globalization) and the vehicle fleet continued

[9] Liquified natural gas (LNG) and compressed natural gas (CNG).

to expand (Figure 1). This decoupling suggests a notable improvement in energy efficiency and/or changes in vehicle utilisation patterns.

The composition of the energy mix also evolved in response to policy interventions. However, the implementation of binding European objectives - notably those set by RED I and its subsequent iterations with associated penalties for non-compliance - stimulated greater demand for alternative fuels. This regulatory push led to bioliquids overtaking natural gas consumption in less than a decade, largely due to their "drop-in" nature, which facilitates blending with traditional fossil fuels without requiring major changes to the existing vehicle fleet or infrastructure. Similarly, the gradual adoption of battery electric vehicles, though still small in scale, has been catalyzed by national policy initiatives such as the government's Ecobonus, which incentivizes the purchase of low-emission vehicles.

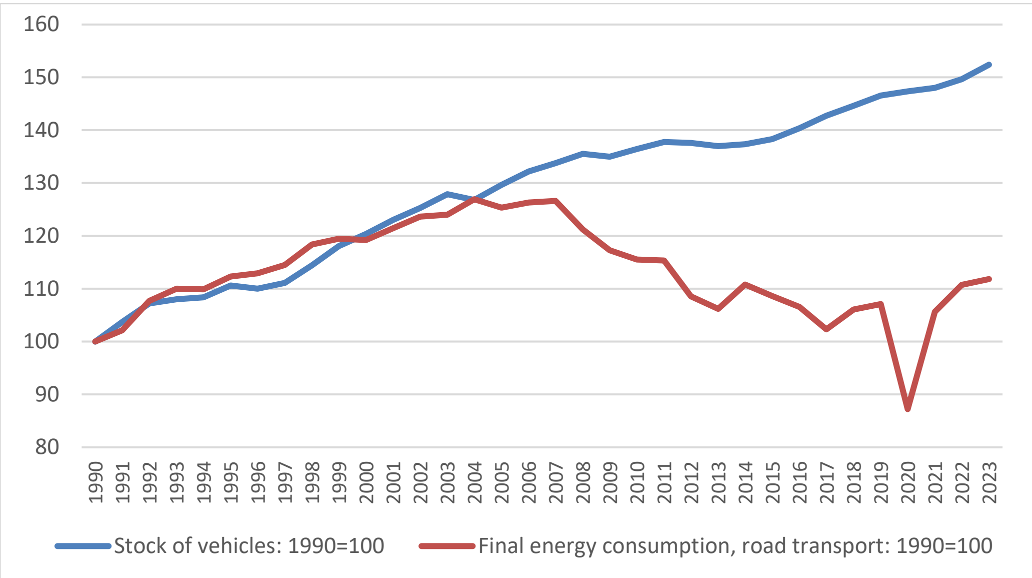

Figure 1. Stock of vehicles and final energy consumption of road transport in Italy: 1990-2023. Source: our elaborations on ACI data and Eurostat statistics. Last accessed February 2025.

In 2023, despite progress in alternative fuels, conventional fossil fuels still predominated, satisfying 95% of the over 34.5 Mtoe consumed by road vehicles. This consumption was primarily split between diesel (64%), gasoline (25%), LPG (5%), and natural gas (1%). Both drop-in biofuels and electricity made only marginal contributions, with biofuel blending levels generally low compared to the EU average, with the exception of biomethane.

Table 2. Ranking of Energy Sources Consumed in Italian Road Transport: 1990-2023. Source: our elaborations on Eurostat statistics and GSE data.

Ranking	1990	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2019	2020-2023	2023
1	Diesel	Gasoline	Gasoline	Diesel	Diesel	Diesel	Diesel	Diesel	Diesel
2	Gasoline	Diesel	Diesel	Gasoline	Gasoline	Gasoline	Gasoline	Gasoline	Gasoline
3	LNG	LNG	LNG	LNG	LNG	LNG	LNG	LNG	Biofuels
4	Natural gas	Natural gas	Natural gas	Natural gas	Natural gas	Biofuels	Biofuels	Biofuels	LNG
5	-	-	-	Biofuels	Biofuels	Natural gas	Natural gas	Natural gas	Natural gas
6	-	-	-	-	-	Electricity	Electricity	Electricity	Electricity

The overall increase in mobility demand, evident in both passenger and road freight transport, represents a key driver of energy consumption (cfr. ISPRA, 2024). However, this rising demand has been partially mitigated by the policy-driven improvements in vehicle energy efficiency, a shift in the energy mix towards renewables, and nascent changes in mobility choices, such as modal shifts to rail and public transport. The increasing share of electrified vehicles (with a 1:99 ratio of electrified to

ICE vehicles by 2022) and the ongoing renewal of the fleet with more efficient vehicles also contribute to tempering the growth in emissions.

4. Methodology

Historia magistra vitae[10], wrote Cicero, seeing history as a guide for life. Machiavelli echoed this idea, using the past to understand the present[11]. Both viewed historical knowledge as key to shaping the future. In this section, we will provide a detailed explanation of the methodology used.

4.1 Grey forecasting models

The future dynamics of a variable can be estimated using deterministic or data-driven models[12]. The latter approach, among the others, has been shown to provide more realistic forecasts (Javed et al., 2020).

Grey forecasting models are one of the most interesting time-series data-driven estimation techniques (Suganthi and Samuel, 2012). They are effective tools for managing uncertainty, particularly in contexts characterized by limited data availability. Introduced by Deng in the early 1980s, these models emerged as a response to the need to address real-world problems for which traditional statistical approaches are not applicable due to insufficient data. The advantages of grey models extend beyond their ability to operate with small datasets: they do not require assumptions about the probability distribution of the historical data under analysis and have proven to be suitable for both short- and long-term forecasting (Kumar and Jain, 2010; Ofosu-Adarkwa et al., 2020).

Table 3. Studies involving forecasts of renewable fuels used in road transport.

Year	Region/Country	Product	Estimated variable	Literature
2008	United States, EU-25, Japan, China, Brazil	Bioethanol	Consumption	Walter et al. (2008)
2009	India, China, Thailand and South Africa	Bioliquid	Production	Hoogeveen et al. (2009)
2013	Denmark	Bioliquids	Demand	Larsen et al. (2013)
2014	Turkey	Bioliquids	Demand	Melikoglu (2014)
2015	Brazil	Bioethanol	Demand	Guerra et al. (2015)
2018	India	Bioethanol	Demand	Sakthivel et al. (2018)
2019	Brazil	Bioliquids	Demand	Junior et al. (2019)
2019	USA	Bioliquids	Production	Yu et al. (2019)
2020	Unites States, China e India	Bioliquids	Production, consumption e self-sufficiency	Javerd et al. (2020)

Deb et al. (2017), in a comprehensive review of forecasting techniques for energy consumption, found that between 2003 and 2015, approximately 13 studies employed grey forecasting methods the energy sectors. Applications of this technique in energy sectors continue to expand. The latest publication is that of (D'Amico et al., 2024)[13]. Concerning biofuels, the most recent uses are listed in Table 3. Javed et al. (2020) used them to forecast the self-sufficiency of the United States, China, and India in liquid biofuels until 2028, while Yu et al. (2022) predicted monthly bioliquid production in the United States until 2030. Other studies have used grey models to project the demand for liquid biofuels in countries like Brazil, India, Turkey, and Denmark (Junior et al., 2019; Sakthivel et al., 2018; Guerra et al., 2015; Melikoglu, 2014; and Larsen et al., 2013). Walter et al. (2008) applied them to estimate bio-gasoline

[10] Cicerone Marco Tullio (55-54 a.C), *De Oratore*.
[11] Machiavelli Niccolò (1513), *Il Principe*.
[12] Data-driven estimation is achieved by applying machine-learning techniques that predict (attempt to predict) the future dynamics of a phenomenon based on its past. For more specifics see (Deb et al., 2017).
[13] Other applications are in Ofosu-Adarkwa et al. (2020), Yu et al. (2022), Ma et al. (2020), Wang and Song (2019), Wu et al. (2018), Kumar and Jain (2010) and Lu et al. (2009).

demand in major markets such as the USA, EU-25, Japan, China, and Brazil, and Hoogeveen et al. (2009) used them to predict biofuel production in India, China, Thailand, and South Africa.

The reasons for the success of grey models are straightforward. Since its beginnings, grey systems theory has aimed to create mathematical models that can predict the dynamics of a variable even in the presence of uncertain or incomplete information (Julong, 1989). According to grey theory, data are not white (perfectly informative) or black (devoid of any information), but "grey" in the sense that they consist of an informative as well as of an unknown part. Instead of ignoring or eliminating uncertainty, grey models try to incorporate it into their structure. How? Since uncertainty creates clutter in the data, grey prediction models use accumulation and inverse differentiation techniques to transform initial data into more regular, "smoother" (monotonic) sequences with a clearer trend. This facilitates the detection of latent patterns and mathematical modeling. Unlike other estimation techniques, grey models are deliberately kept simple. Simplicity avoids over-fitting of the data, distortions, and facilitates the identification of the actual trend of the studied phenomenon. According to grey theory, it is not (always) necessary to have a large amount of precise data to make useful predictions: meaningful information can be extracted even from a few grey data. In fact, grey models can extract useful indications on the future trend of the variable of interest from limited datasets (4-10 observations) and can be used (with certain caveats) to make both short-term and medium-term estimates.

The fundamental grey models[14] can be adapted and combined to address a variety of complex problems. As there are no previous applications of grey forecasting models to the estimation of alternative fuel consumption in the Italian road transport sector, it was first necessary to identify the most appropriate grey model for this context. Following the methodology of Javed et al. (2020), we employed a combination of models: the classic EGM (1,1), its optimized version, the EGM (1, 1, α, θ), and the DGM (1,1). The detailed formalizations of the models used are provided in the subsections below.

4.2 EGM (1,1) and EGM (1, 1, α, θ)

EGM (1,1) is the even form of a grey model with first-order differential equation containing a single variable. It is suitable for making predictions using non-exponentially increasing data sequences (Liu et al., 2017). The formalization of the EGM (1,1) model involves a series of steps to transform the original data into a format suitable for forecasting. Let

$$X^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\right\} \tag{1}$$

be the original non-negative sequence of data[15] where, $x^{(0)}(k)$ denotes the k-th raw data value, and n is the number of data points ($4 \leq n \leq 10$). To smooth out the randomness and extract the underlying trend from the data, a cumulative sum operator is applied. This is known as the once accumulating generation operator (1-AGO). The resulting sequence is:

$$X^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)\right) \tag{2}$$

[14] The one-variable first-order grey model; the N-variable first-order grey model; the N-variable zero-order grey model; and the Verhulst or one-variable second order grey model. For formalizations see, for example, Xuemei et al. (2019). For further technical details on grey estimation models see, for example, Xie and Wei (2024).

[15] In our case, the initial data are represented by the consumption of biodiesel, bio-gasoline, biomethane, and electricity for Italian road transport from 2016 to 2023 ($k = 1,2,3, \dots, 8$ and $n = 8$).

where each element is the sum of the preceding raw data points: $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$ and $k = 1,2,\dots,n.$ Next, the sequence $Z^{(1)}$ is constructed from $X^{(1)}$. $Z^{(1)}$ is the average of consecutive neighbours and is used to further stabilises the data and reduce noise. Formally:

$$Z^{(1)} = \left(z^1(1), z^1(2) \dots \dots z^1(n)\right), \tag{3}$$

where $z^1(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1)$ and $k = 2,3,..n$. The core of the EGM (1,1) model is the first-order grey differential equation. It relates the original (raw) data to the mean generated sequence and is expressed as:

$$x^{(0)}(k) + az^{(1)}(k) = b. \tag{4}$$

Equation (4) describes the evolution of the system over time, where a and b are the grey model parameters:

- a is the development coefficient, which reflects the rate of growth or decline.
- b is the grey action quantity, which represents the system's internal change.

The parameters a and b can be estimated using the Ordinary Least Squares (OLS) method. The matrix form for the parameter estimation is:

$$[a, b]^T = [B^T B]^{-1} B^T Y \tag{5}$$

where,

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ .. & .. \\ -z^{(1)}(n) & 1 \end{bmatrix} \text{ and } Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \dots \\ x^{(0)}(n) \end{bmatrix}.$$

Once the parameters a and b are determined, the time response equation of the EGM (1,1) model can be established. This equation is the solution to the differential equation, and it is used to forecast the values of the cumulative sequence, $\hat{x}^{(1)}(k)$:

$$\hat{x}^{(1)}(k) = \left(x^{(0)}(k) - \frac{b}{a}\right) e^{-a(k-1)} + \frac{b}{a}. \tag{6}$$

Finally, to obtain the predicted values of the original data sequence $\hat{x}^{(0)}(k)$, the cumulative prediction is reversed using the inverse operation of the 1-AGO. By substitution, we can find the time response sequence which is showed below:

$$\hat{x}^{(0)}(k) = (1 - e^{a}) \left(x^{(0)}(1) - \frac{b}{a}\right) e^{-a(k-1)}. \tag{7}$$

The application of the 1-AGO presents certain limitations that hinder its use in complex situations. In this regard, Javed et al. (2020) proposed the optimized EGM (1, 1, α, θ) model. Following the guidelines of Ma et al. (2020), Javed et al. (2020) introduced a conformable fractional accumulation operator:

$$X^{(\alpha)} = \left(x^{(\alpha)}(1), x^{(\alpha)}(2), \dots, x^{(\alpha)}(n)\right), \tag{8}$$

where $x^{(\alpha)}(k) = \sum_{i=1}^{k} \frac{x^0(i)}{i^{i-\alpha}}, \quad k = 1,2, \dots, n \; and \; \alpha \in (0; 1]$.
Moreover, unlike the classic EGM (1,1), where the background value is calculated as the average of two consecutive data points and following Niu et al. (2006), Javed et al. (2020) applied the concept of interval number whitening, which consists of a weighted background value:

$$Z^{(1)} = \left(z^1(1), z^1(2) \dots \dots z^1(n)\right) \tag{9}$$

where $z^1(k) = \ \theta x^{(\alpha)}(k) + (1 - \ \theta)x^{(\alpha)}(k-1) \; and \; \theta \epsilon [0; 1]$.[16]
The first-order grey differential equation - and therefore the evolution of the system over time - is as in (4). The fitted values of the cumulative sequence and of the raw data are

$$\hat{x}^{(\alpha)}(k) = \left(x^{(0)}(1) - \frac{b}{a}\right) e^{-a(k-1)} + \frac{b}{a} \tag{10}$$

and

$$\hat{x}^{(0)}(k) = k^{1-\alpha} \left(\hat{x}^{(\alpha)}(k) - \hat{x}^{(\alpha)}(k-1)\right), \tag{11}$$

respectively, where $k = 1,2, \dots n$ and $\hat{x}^{(0)}(0) = 0$. The time response sequence for the original variable is:

$$\hat{x}^{(0)}(k) = k^{1-\alpha}(1 - e^a) \left(x^{(0)}(1) - \frac{b}{a}\right) e^{-a(k-1)}.$$

In EGM($1,1,\alpha,\theta$), α and θ are selected to minimize the Mean Absolute Percentage Error between raw and predicted data. The strength of the model proposed by Javed et al. (2020) is that the parameters α and θ are not static, but dynamic, thus allowing greater adaptability to different forms of error and, consequently, more precise estimates. Further information on the characteristics and parameters of these models is available in the key reference studies by Liu et al. (2017) and Ma et al. (2020).

4.3 DGM (1, 1)

The DGM(1,1) is a discrete grey model with a first-order differential equation containing a single variable. According to Liu et al. (2017), it is suitable for making predictions based on a homogeneous exponential data sequence. Let $X^{(0)}$ and $X^{(1)}$ denote the original (raw) data and the 1-AGO sequence, respectively (see Section 4.2). The DGM (1,1) model is founded on a discrete-time difference equation, rather than a continuous differential equation, which constitutes the core difference from the EGM (1,1) model. The equation is a simple linear recurrence relation:

$$x^{(1)}(k+1) = \ ax^{(1)}(k) + \ b \tag{12}$$

where a and b are the model parameters that can be estimated – as before - using the OLS method as in Section 4.2. Once the parameters a and b are determined, the forecast for the cumulative sequence can be obtained recursively using the discrete grey differential equation:

$$\hat{x}^{(1)}(k) = a^k \left(x^{(0)}(1) - \frac{b}{1 - \ a}\right) + \frac{b}{1 - a}, where \quad k = 2,3, \dots n \tag{13}$$

[16] Assuming α=1 and θ=0.5 we would get back to the standard EGM(1,1).

and the forecasted values for the original data sequence, $\hat{x}^{(0)}(k)$, are recovered by applying the inverse 1-AGO operation:

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1), where \quad k = 1,2,\ldots n \quad and \qquad \hat{x}^{(0)}(0) = 0 \quad (14)$$

The forecasted values for the future time points are obtained applying the time-response function

$$\hat{x}^{(0)}(k) = (a-1)\left(x^{(0)}(1) - \frac{b}{1-a}\right)a^{k-1}. \qquad (16)$$

Further information on the characteristics and parameters of these models is available in the key reference studies by Liu et al. (2017), and Xie and Liu (2005).

4.4 Forecasting metrics

Following the methodology of Javed et al. (2020), five metrics were used for the performance evaluation of the models: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Normalized RMSE (NRMSE), Mean Absolute Percentage Error (MAPE), and Normalized MAPE (NMAPE). A detailed description of these metrics can be found in Ahmed et al. (2020). The formulas for the metrics are as follows:

1. Mean Absolute Error

$$MAE = \frac{1}{n} \times \sum_{k=1}^{n} |x(k) - \hat{x}(k)|$$

2. Root Mean Square Error

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(x(k) - \hat{x}(k)\right)^2}$$

3. Normalized RMSE

$$NRMSE = \frac{\sqrt{\sum_{k=1}^{n}\left(x(k) - \hat{x}(k)\right)^2}}{\sqrt{\sum_{k=1}^{n}\left(x(k)\right)^2}}$$

4. Mean Absolute Percentage Error

$$MAPE(\%) = \frac{1}{n} \times \sum_{k=1}^{n} \left|\frac{x(k) - \hat{x}(k)}{x(k)}\right| \times 100$$

5. Normalized MAPE

$$NMAPE(\%) = \frac{1}{n} \times \sum_{k=1}^{n} \left|\frac{x(k) - \hat{x}(k)}{\frac{1}{n}\sum_{k=1}^{n} x(k)}\right| \times 100$$

where $x(k)$, $\hat{x}(k)$, k and n are as defined in Sections 4.2 and 4.3. As indicated by Javed et al. (2020), MAPE has widespread application in various forecasting contexts. In general, a MAPE result below 20% indicates good forecasting quality, a result exceeding 20% but less than 50% suggests reasonable quality, and a result of 50% or higher is inaccurate.

5. Data

According to EEA, in 2023, road transport was responsible for 26% of net GHG emissions in EU-27. Over 13% of these emissions were generated by the movement of people and goods on Italian roads. While the EU-27 saw a 1% average reduction in road transport's GHG emissions between 2022 and 2023, Italy recorded a 0.5% rise. Therefore, analysing the prospects for using energy sources alternative to traditional fossil fuels in Italian road transport is of particular interest given both national and European objectives. Eurostat publishes annual statistics on final energy consumption by fuel type and sectors over the period 1990 to 2023. Data concerning the use of alternative fuels as a substitute for traditional fossil fuels first became available in 2004 (see Section 3). Since 2010, data has been collected on electricity consumption in the road transport sector.

Table 4. Consumption of alternative fuels in Italy's road transport: 2016-2023. Source: Eurostat & GSE.

	Bio-gasoline	Biodiesel	Biomethane	Electricity
2016	32,54	1.008,34	0,02	5,93
2017	33,06	1.028,68	0,15	7,13
2018	32,61	1.217,08	0,45	8,51
2019	30,44	1.245,66	40,91	11,74
2020	19,64	1.245,08	82,09	16,37
2021	27,09	1.388,39	136,54	37,88
2022	34,99	1.352,78	184,87	51,53
2023	85,10	1.416,20	225,21	70,35

Initial data on alternative fuels exclusively focused on first-generation biofuels, which have questionable environmental benefits compared to traditional fossil fuels. Additionally, until 2016, the portion of biomethane, allocated to road transport was a fixed percentage of total national biomethane, inputs. This methodology is not well-suited to the specific characteristics of Italian road transport, where the use of this energy source is higher than the EU average.

For our simulations, we used annual consumption data for biodiesel, bio-gasoline, biomethane, and electricity in road transport from Eurostat and GSE (2025) for the period 2016-2023. The detailed data (in ktep) can be found in Table 4.

6. In-sample forecasts and the selection of the model

For each energy carrier, Figure 3 illustrates the observed values alongside the estimates generated by the selected models: EGM (1, 1, α, θ), EGM (1,1) and DGM (1,1). The values of the metrics used for the performance evaluation of the models are shown in Table 5.

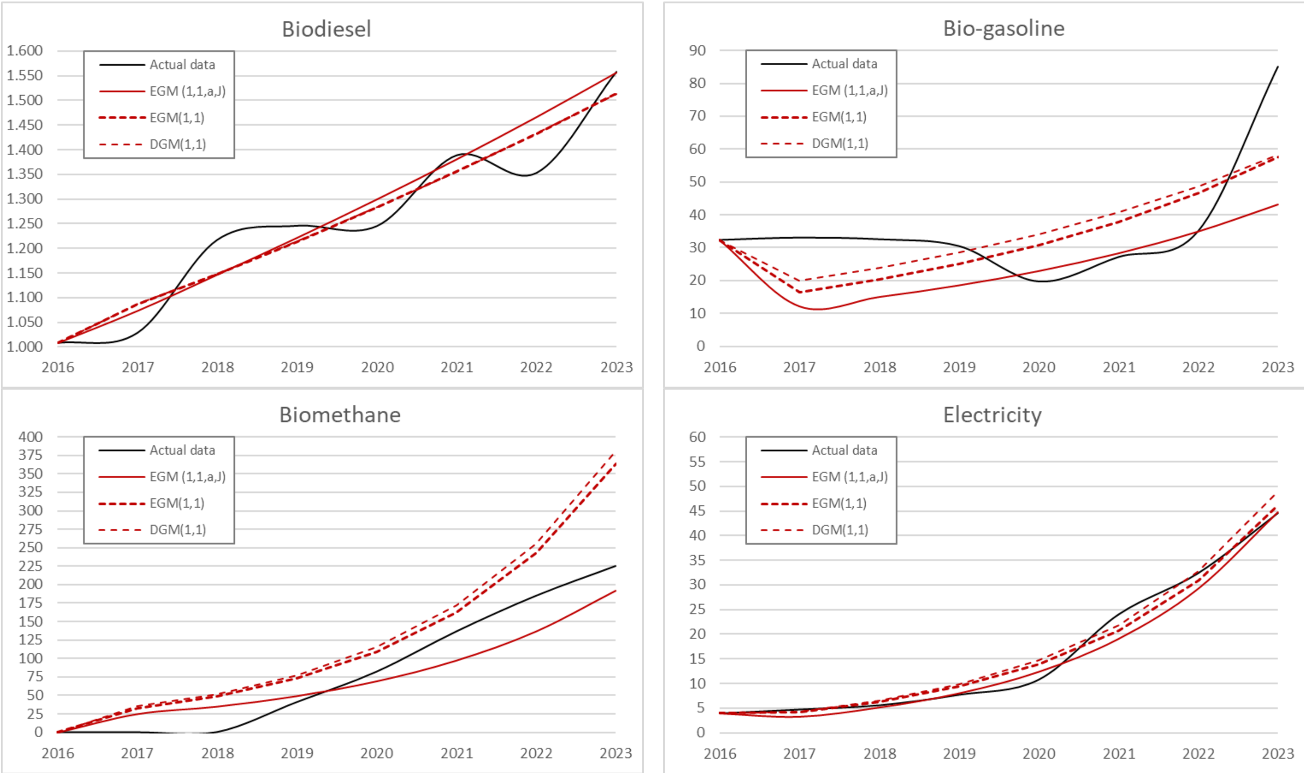

Figure 3 - Consumption of biodiesel, bio-gasoline, biomethane and electricity: actual data and grey models' forecasts (ktep). Data source: Eurostat and GSE. Last accessed February 2025.

Table 5. Goodness-of-fit indicators.

	MAPE (%)	NMAPE (%)	RMSE	NRMSE	MAE
Biodiesel consumption					
EGM (1,1,α,θ)	3.17	3.13	54.33	0.04	39.33
EGM(1,1)	3.49	3.51	49.79	0.04	44.02
DGM(1,1)	3.49	3.51	44.02	49.79	0.04
Bio-gasoline consumption					
EGM (1,1,α,θ)	28.35	32.79	18.22	0.44	12.10
EGM(1,1)	33.57	32.38	14.10	0.34	11.94
DGM(1,1)	33.41	31.32	13.94	0.34	11.55
Biomethane consumption					
EGM (1,1,α,θ)	30.97	29.98	29.53	0.25	25.12
EGM(1,1)	41.16	54.09	59.56	0.50	45.32
DGM(1,1)	44.05	62.17	67.61	0.57	52.08
Electricity consumption					
EGM (1,1,α,θ)	11.40	9.57	3.73	0.11	2.50
EGM(1,1)	13.05	10.11	3.25	0.09	2.65
DGM(1,1)	14.83	11.88	4.25	0.12	3.11

The EGM(1, 1, α, θ) model consistently demonstrated superior performance over the other grey models with respect to in-sample forecast accuracy. This conclusion is supported by the model's performance across the five metrics evaluated in the study (Table 4). Furthermore, a clear hierarchy of forecasting accuracy was identified for the different alternative fuels:

- Biodiesel consumption was forecasted with the highest degree of accuracy.
- Electricity consumption exhibited the second-highest accuracy.
- Bio-gasoline consumption followed in third place.
- Biomethane consumption was the least accurately forecasted.
-

7. Out of sample forecasts: the use of alternative fuels in Italy's road transport (2030)

According to grey models, by 2030, alternative energy sources are projected to supply Italy's road transport sector with approximately 5 Mtoe, a threefold increase from 2022 levels. The projected energy mix is composed of biodiesel (50%), electricity (25%), and biomethane (20%).

The analysis indicates a rapid expansion of alternative energy carriers. Electricity consumption in the road transport sector is expected to increase tenfold by 2030, while natural gas is forecast to be completely replaced by its renewable counterpart, biomethane. This would make natural gas the first 100% renewable fuel in Italy. However, by as early as 2028, the growth in biomethane consumption could be constrained by a lack of demand. Without an increase in new CNG vehicle registrations, additional supply would need to be absorbed by other sectors/countries.

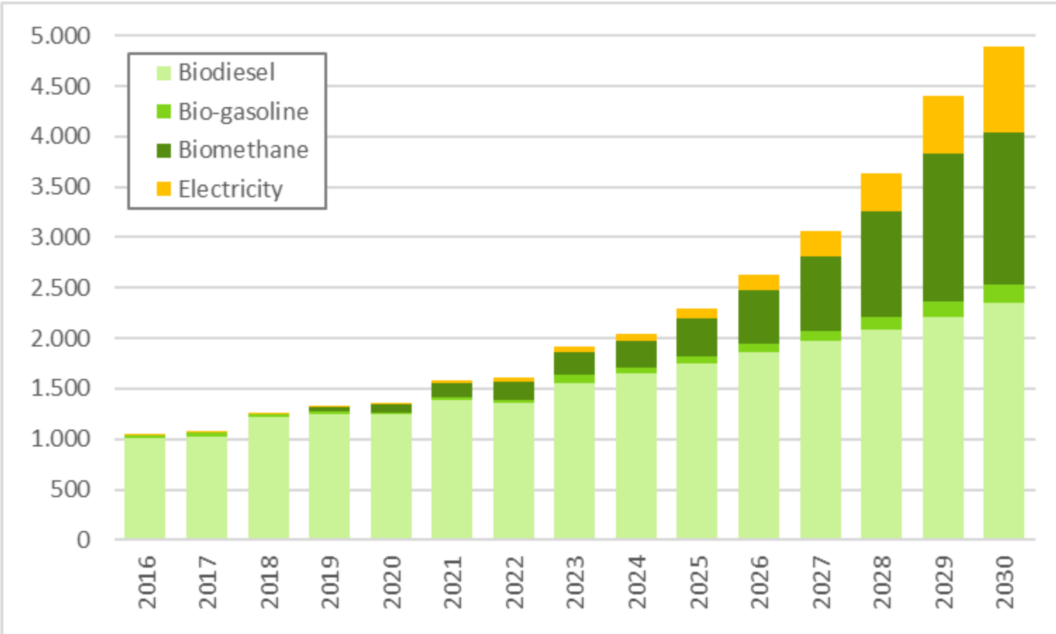

Figure 4 – Forecasted consumption of biodiesel, bio-gasoline, biomethane and electricity in Italy's road transport up to 2030 (ktep).

Based on an analysis of data from 2016 to 2023, grey models predict that bio-gasoline consumption will increase sixfold by 2030 compared to 2022 levels. However, this forecast likely underestimates future consumption because it does not account for recent regulatory changes. Beginning in 2023, a mandatory blending requirement was implemented, with a more stringent 5% obligation set for 2030. Consequently, the non-fossil gasoline consumption projected by the models should be seen as a minimum baseline, as it only reflects consumption trends prior to these policy mandates. Given a road transport gasoline consumption of 9 Mtoe, a 5% blending requirement would necessitate a supply of 450 ktoe, which is more than twice the amount our models projected.

8. Comparing Grey Forecasts with NECP 2024 Targets for 2030

To ensure a robust comparison between the grey model forecasts and the data reported in Italy's NECP, we have implemented several methodological adjustments to NECP figures. These adjustments were necessary to align the data sets, as the government document does not differentiate between certain fuel types. First, NECP figures were adjusted to refer exclusively to the use of renewable energy carriers in road transport. We have deliberately excluded RFNBO and RCF from our analysis, as grey models could not forecast these given the lack of historical data. Second, while the NECP only accounts for renewable electricity, our analysis required the inclusion of both renewable and fossil-derived electricity consumed in road transport. Consequently, the NECP data for electricity was modified to reflect this total. Finally, the Italian government document does not distinguish between biodiesel and bio-gasoline consumption. Therefore, to facilitate a direct comparison, we have aggregated our forecasts for these fuels to match the NECP's combined reporting for bioliquids.

The analysis shows that the grey models' forecasts are more conservative than the NECP's targets (Figure 5 and 6). The models predict a combined contribution of approximately 5 Mtoe from the four energy carriers (biodiesel, bio-gasoline, biomethane, and electricity), which is about 80% of the NECP's target. The most significant gap between the data-driven forecasts and policy targets lies in liquid biofuels, which the NECP relies on to meet 65% of the overall target - 15 percentage points more than what grey models project. This discrepancy is likely due to grey models' inability to incorporate the effects of recent mandatory bio-gasoline input obligations.

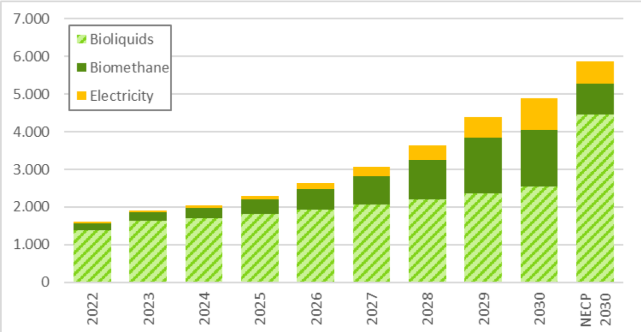

Figure 5 - A comparative analysis of alternative fuel consumption projections for Italian road transport to 2030: Grey Forecasts vs. NECP 2030 Targets (in ktep).

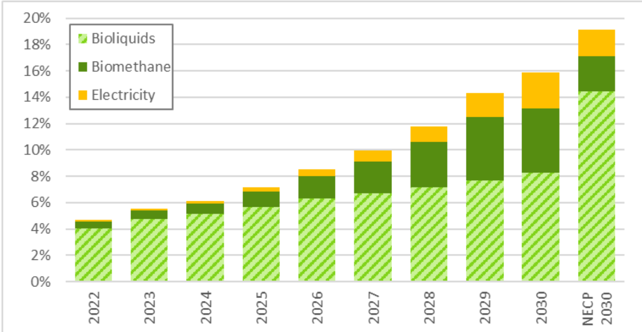

Figure 6 - Percentage share of liquid biofuels, biomethane, and electricity in final energy consumption for Italy's road transport: Grey Forecasts vs. NECP 2030 target.

In contrast, grey models predict electricity use that is largely in line with, and potentially even exceeds, that predicted by the NECP. This suggests that the increasing use of electrified vehicles is a widely supported trend, regardless of the specific vehicle numbers.

The lack of a detailed breakdown in the NECP prevents a direct comparison of biomethane consumption, but the grey models predict that it will fully replace its fossil counterpart by 2030, becoming Italy's first 100% renewable fuel.

Ultimately, the forecasts from grey models indicate that alternative fuels will satisfy approximately one-sixth of the final energy demand for road transport by 2030. In contrast, meeting the ambitious targets in the NECP would lead to a one-fifth contribution. While both outcomes represent a significant improvement over the current 5% share, neither trajectory is sufficient to achieve the two-fifths contribution needed to align with the EU's climate objectives.

9. Concluding remarks and future outlook

From a data-driven perspective, this study provides a novel assessment of Italy's road transport decarbonisation trajectory by 2030, leveraging grey forecasting models. The analysis, which is the first of its kind to apply this methodology to the Italian context and to a broad mix of alternative fuels, offers a critical perspective on the feasibility of the ambitious targets set forth in the latest NECP. Our findings suggest a clear, albeit challenging, path for the country, in which progress is evident but remains insufficient to meet the most ambitious European goals without further, significant, additional intervention.

The grey models predict a substantial increase in the consumption of alternative fuels (biodiesel, biogasoline, biomethane, and electricity), reaching approximately 5 Mtoe by 2030. This represents a threefold rise from 2022 levels, indicating a tangible shift away from a fossil-fuel-dominated energy mix. Notably, our forecasts show that biomethane is on a path to entirely replace its fossil counterpart, becoming a fully renewable energy source for road transport. Similarly, the projected consumption of electricity is robust, aligning with and in some scenarios exceeding the NECP's targets. This convergence of data-driven forecasts and policy objectives in the electrical domain points to a growing consensus on the role of electrified vehicles in the future of transport.

A gap emerges in the case of liquid biofuels. While they represent (and will continue to represent) the primary renewable alternative to fossil fuels in the short to medium term, the models suggest that their growth, though significant, could be below the Italian regulator's expectations. This discrepancy is likely due to two key factors. Firstly, as data-driven estimates, the models do not fully internalise the effects of the very latest regulations, such as the new mandatory blending obligations for biogasoline introduced in 2023. Secondly, the future of these fuels is still subject to European regulatory uncertainty. What market will bio-gasoline and biodiesel have from 2035 onwards? While directives like the RED continue to promote the use of advanced biofuels, even providing for them the same valorisation as renewable fuels of non-biological origin, Regulation (EU) 2023/851 has not – to date – extended the e-fuels exemption to advanced biofuels. The persistence of this situation of uncertainty and regulatory ambiguity will inevitably affect investment decisions, with consequences for production and consumption dynamics across the Union.

In a broader context, the analysis reveals a fundamental disconnect. While the grey models forecast a considerable increase in the use of alternative fuels, they also show that even this progress is not enough to put Italy on the path to meeting its climate commitments. By 2030, alternative fuels are projected to satisfy only one-sixth of the final energy demand for road transport, a commendable improvement but still far short of the two-fifths share needed to align with the EU's broader decarbonisation objectives. Furthermore, the findings highlight a paradoxical situation in which the decarbonisation of road transport consumption is outpacing the electrification of the vehicle fleet. The stark reality of the current vehicle stock - with fewer than 400,000 electric cars in late 2024 compared to the 4.3 million estimated for 2030 in the NECP - illustrates the immense challenge that lies ahead for Italy.

In conclusion, Italy's journey towards decarbonising road transport is at a pivotal juncture. The EU's increasingly stringent regulatory framework and the country's ambitious NECP provide a clear strategic direction, yet our forecasts suggest that current trends will not be sufficient on their own. The achievement of the NECP's goals will hinge not only on policy-driven incentives but also on overcoming significant challenges related to the large-scale production of sustainable fuels, the development of robust charging and refuelling infrastructure, and a widespread shift in consumer and industry behaviour. While the path is challenging, our work provides a solid, data-driven foundation for policymakers and stakeholders to understand the current trajectory and to identify the areas where additional measures are most critically needed to transform a strategic vision into a tangible reality.

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