System dynamics-based assessment of novel transport options adoption in India

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Abstract
The adoption of novel transport options such as ethanol blended fuel (E85) vehicles, electric vehicles (EV), and compressed natural gas (CNG) vehicles to replace conventional petrol (gasoline) and diesel vehicles is not yet well understood. This work develops a system dynamics (SD) model to study the adoption of these novel options for private transport needs in India as a function of technology performance, cost, and other sector specific features. For EVs, expected growth in battery technology and the inconvenience due to lack of charging infrastructure are considered. Since ethanol production sector is still scaling up, model captures the inter-relationships between demand, supply, producer’s profit, and investment in capacity increase. The growth in compressed biogas (CBG) plants and inconvenience due to lack of gas refilling stations are considered for CNG vehicles. For petrol and diesel, the effect of demand on consumer prices and its effect on ownership cost is modelled. A multi-multinomial logit model is used to capture selection of transport option as a function of total ownership costs. Model simulations are performed till 2050, and quantify the adoption trends as well as resulting total greenhouse gas emissions considering life cycle perspective for all the technological options. Simulation results show that E85, EVs and CNG vehicles would constitute 34 % of total private vehicle stock by 2050, resulting in 668.75 million tonnes of CO2 emissions. The targets set by the government for EV adoption and blending rate of ethanol will not be achieved, and significant improvement in costs and infrastructure are needed. Various policy options to improve adoption of new options are explored, identifying the technology development targets.

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**Abbreviations**

**Parameters**

- $S$: Saturate vehicle ownership per 1000 population
- $v$: Scale parameter
- $C_e$: Ethanol deficit coefficient
- $P$: Additional costs included above the refinery gate price of ethanol
- $s_{ratio}$: Ideal number of gas refilling stations corresponding to CNG vehicle stock
- $k_{per plant}$: Number of gas refilling stations per CBG production plant
- $CNG_{factor}$: Scale up factor to account for non-uniform distribution of gas refilling stations

**Variables**

- $C$: Vehicle ownership per 1000 population
- $\mu$: GDP per capita
- $P_n$: Purchase probability of $n^{th}$ vehicle option
- $OC_n$: Ownership cost of $n^{th}$ option
- $P^i$: Petrol price in INR/litre at time step $i$
- $D^i$: Diesel price in INR/litre at time step $i$
- $C^i$: Brent crude oil price in INR/litre at time step $i$
- $D_p^i$: Petrol demand in litre at time step $i$
- $D_d^i$: Diesel demand in litre at time step $i$
- $EP^i_m$: Ethanol production capacity from molasses in litres at time step $i$
- $EP^i_b$: Ethanol production capacity from lignocellulosic biomass in litres at time step $i$
- $P^i_m$: Profit earned by molasses based biorefineries in INR at time step $i$
- $P^i_b$: Profit earned by lignocellulosic biomass-based biorefineries in INR at time step $i$
- $RP^i_m$: Refinery gate price of ethanol from molasses in INR/litre at time step $i$
- $RP^i_b$: Refinery gate price of ethanol from lignocellulosic biomass in INR/litre at time step $i$
- $TC^i_m$: Production cost of ethanol from molasses at time step $i$
- $TC^i_b$: Production cost of ethanol from lignocellulosic biomass at time step $i$
- $ED^i$: Ethanol deficit (volume) at time step $i$
- $w^i_m$: Weighted average ethanol produced from molasses at time step $i$
- $w^i_b$: Weighted average ethanol produced from lignocellulosic biomass at time step $i$
- $E^i$: Ethanol price in INR/litre at time step $i$
- $I^i$: Inconvenience cost due to insufficient charging stations in INR
- $EV^i_d$: Ideal number of charging stations
- $EV^i_{ac}$: Existing number of charging stations
Introduction

India is the third-largest greenhouse gas (GHG) emitting country in the world (Joshi and Chen 2020). India’s total GHG emissions in 2019 were 132 Mt CO$_2$e, while the per capita emissions were 1.94 ton CO$_2$e, which were less than half the global average of 4.2 ton CO$_2$e (Joshi and Chen 2020). In order to build a low carbon future, Nationally Determined Contributions (NDC) of India aim to achieve 33–35% reduction in greenhouse gas (GHG) emission intensity by 2030 compared to 2005 level (Joshi and Chen 2020). Sustainable and green transportation is one of options to achieve this ambition (UNFCCC 2015). Transport sector is the third largest CO$_2$ emitting sector in India (Singh et al. 2019). Socio-economic development and increased migration to cities have resulted in the expansion of the transport sector (Pinna et al. 2014). This is evident from the fact that travel demand has increased by almost 8 folds between 1980 and 2016 (NITI Aayog and Boston Consulting Group 2018). Amongst the road and rail passenger transport modes, the growth in demand of road passenger transport using two-wheelers, cars, three-wheelers, and buses was the highest at 11% between 2000 and 2012 (Singh et al. 2019). However, larger part of road passenger transport demand rose due to rapid increase in private vehicle ownership, which includes cars and two-wheelers. The number of registered cars and two-wheelers increased by fourfold from 43.8 million in 2000 to 178.1 million in 2015 (Ministry of Statistics and Programme Implementation 2017). In addition to dominating the travel demand, road transport sector is responsible for 73–80% of transport sector emissions (Singh et al. 2019). With continued population growth and economic development, private vehicle ownership is expected to increase in future resulting in increased energy demand and CO$_2$ emission from transport sector (Dhar et al. 2018). Therefore, transition to more sustainable transport options for road transportation is very important to achieve aforementioned GHG emission reduction targets.

The Indian government has proposed ambitious targets regarding electric vehicles (EVs) adoption, ethanol (biofuel) blending, and production of compressed biogas (CBG) to replace fossil natural gas as transport fuel. Faster Adoption and Manufacturing of EV (FAME) policy of 2018 targets 30% share of EVs in new vehicle sales by 2030, and benefits of such a transition have been reported in multiple studies. A study by NITI Aayog assumed 55% share of electric cars and two-wheeler in new vehicle sales by 2030, leading to savings of 474 Mt of oil and 846 Mt CO$_2$ emissions (NITI Aayog and RMI 2019). Another study by TERI assumed 20% share of electric two-wheelers in new sales by 2030, thereby saving 4% of GHG emissions and 5% of energy (TERI 2019). The government has also proposed to provide subsidies on purchase of EV under FAME scheme. On biofuels front, 20% blending of ethanol in petrol (gasoline) by 2030 was proposed through the National Policy on Biofuels 2018. Recently, this target was moved ahead to 2025 based on the strong upsurge in ethanol blending fraction in recent years. Introduction and adoption of blend fuel vehicles, such as, E85 vehicles with 85% blend of ethanol will be essential to achieve this target. Additionally, replacement of compressed natural gas (CNG) from fossil sources with CBG obtained from agricultural waste in CNG driven vehicles is another initiative taken by government. The Sustainable Alternative Towards Affordable Transportation (SATAT) scheme aims to setup 5000 compressed biogas (CBG) plants and 10,000 CBG dispensing stations by 2025, and the CBG will be produced locally using agricultural residue.

Although adoption of these novel transport options is desirable, many challenges need to be overcome. These challenges can be classified into three categories. The first category includes technology related challenges, such as engine modification for E85 vehicles as well as battery weight and charging times for EVs. The second category includes infrastructure related challenges, such as the development of charging and gas refilling infrastructures and transportation of ethanol which is hygroscopic in nature. The third category includes socio-economic challenges such as convenience, affordability, and range anxiety. It is important to understand the impact of these factors on the actual adoption, and the likelihood of these targets being met. This can help in developing appropriate technology development targets as well as policy initiatives.

The ANSWER MARKEL model framework has been used in India for the analysis of climate and energy policies (Dhar et al. 2018; Shukla and Dhar 2016). It is an optimisation model that evaluates the transition to newer vehicle technologies and fuel mix in the transport sector by minimizing the overall system cost. However, the model has certain limitations which need to be acknowledged. In
terms of scope, the model only considers the technology cost while estimating the technology transition and ignores other factors mentioned previously. The model also assumes an unrestricted supply of fuel and thereby ignores the influence of fuel shortage on vehicle adoption. From the methodology standpoint, simplifying assumptions are necessitated to ensure efficient solutions of an optimization model. Any technology selection and transition model, particularly involving a large number of stakeholders, is characterised by complex decision-making equations. These are again difficult to capture through simple algebraic equations as part of an optimization model formulation. Additionally, the presence of nonlinearity creates challenges (Aslam and Ng 2015). Capturing the dynamic impacts of one sector on the other is also important, but dynamic, multi-period optimization models are computationally challenging to solve. Hence, a more flexible modeling approach is needed to study the transition to newer vehicle technologies in the transport sector. The system dynamics (SD) modelling approach is a promising approach that addresses many of these limitations.

Abbas and Bell (1994) highlighted the advantages of the system dynamics modelling approach in transport modelling, particularly its usefulness as a decision support tool for policy analysis. Transport systems are complex, often involving several different stakeholders giving their feedback responses at different time lags. SD modelling offers a holistic systems-based approach for transport planning so that important feedback effects and time lags can be demonstrated to policymakers. Shepherd (2014) reviewed SD modelling applied to the transportation sector, including aspects such as transitioning to alternative fuel vehicles, supply chain management, and strategic policies at the regional level. Struben and Sterman (2008) developed an SD model to study how feedback effects can either enable or constrain the diffusion of alternative fuel vehicles. The study showed that there exists a critical threshold for sustained adoption of alternative technologies which depends on economic and behavioural parameters. It also pointed out that marketing and subsidies must remain for a very long time for diffusion to become self-sustaining. Shafiei et al. (2015) proposed an SD model to study the transition to alternate transport options, i.e., hydrogen and biofuels, by considering the interactions between fuel demand and supply, energy prices, and infrastructure. Simulation results showed a continuous fluctuation between existing and alternate transport options as fuel prices dynamically adjusted based on changes in supply and demand. There have been many system dynamics-based national-level studies to simulate the behavioural growth of industries based on cellulosic ethanol (Bush et al. 2008) and biodiesel (Barisa et al. 2015). The modelling framework for the selection of vehicle options is often defined in SD models as a discrete choice based on the multinominal logit (MNL) model (Vilchez and Jochem 2019). SD models have also been coupled with agent-based models to capture the complexity of the transition towards alternative fuel vehicles, particularly the decision making of individual stakeholders in the system (Pasaoglu et al. 2016). The importance of a qualitative framework for analysing the GHG reduction policies aimed at the transportation sector of the US has been demonstrated by Stepp et al. (2009). The authors suggested that the use of SD modelling provided an insight into the complex causal relations that may diminish the policy effectiveness. In this regard, SD models have been extensively used to analyse the policy implications on the adoption of sustainable transport options (Zhou et al. 2020).

In the Indian context, SD models have been developed to assess specific energy and environmental impacts of EV adoption. Gomez Vilchez et al. (2013) used SD modelling to evaluate the impacts of EV adoption in countries with high motorization rates such as USA, UK, Germany, France, China, and India. They predicted the fuel/energy demand and emissions for Indian transport sector in 2050 and these were calculated as, 50,000 million litres of petrol and diesel demand, 2400 GWh of electricity demand, and 100 Mt CO$_2$e of GHG emissions. Rodrigues et al. (2012) in 2012 developed an SD model to study the effect of rising fuel consumption in India. The findings supported the imposition of carbon tax to regulate fuel consumption in the future. Han et al. (2010) evaluated various policies towards reducing emissions by taking a case study of urban transport sector of Delhi, India. Authors concluded that imposing fuel tax was the most effective instrument towards building an eco-friendly transport sector. Gupta et al. (2019) did a similar study to understand the effect of carbon tax on GHG emission mitigation for Indian road passenger transport. The authors established that carbon tax could potentially reduce CO$_2$ emission in range of 26–40% compared to base case scenario by 2050.

The review indicated that understanding the adoption of multiple novel transport options as an outcome of dynamic behaviour of stakeholders in the transport sector has not been considered. Supply-demand dynamics of fuels, technological advancement in existing and new vehicle models, environmental policies, and public awareness are some of the major factors which will affect the adoption trends. Considering these factors will create likely real-world situation to predict the adoption trend of various vehicle options in transport sector. This work takes a step towards addressing this research gap, and develops an SD model in the Indian context. The model studies the adoption trend of E85, EVs, and CNG vehicles in the private road transport sector in India spanning a time period of 30 years from 2020 to 2050. The research also evaluates different technology development and policy alternatives to achieve targets proposed by the government regarding biofuel blending and EV adoption. The work also quantifies
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the impact of adoption on GHG emissions. This is done by implementing SD methodology, that considers the feedback loops and time delays present in the system, and thus captures the dynamic behaviour of the system. Since SD methodology has been frequently used for long-term forecasting, policy planning and analysis, it is appropriate for the objective of this work. The important contribution of this work and its novelty are summarized here:

- The work has developed a system dynamics model to understand the expected adoption of novel transport options in India. To provide a more realistic assessment of the evolution of the transport sector, the model proposed here has incorporated several novel features which have not been considered in prior studies in the Indian context. These are listed as follows:
  - The important feedback loops determining the annual demand for each vehicle option have been captured in the model.
  - The model has accounted for the inconvenience associated with the adoption of EV and CNG vehicles due to the lack of sufficient refueling infrastructure and long refueling time.
  - The effect of technological advancements on cost reduction of EV batteries and ethanol production processes has been considered.
  - Life cycle emissions of all the transport fuels and EV batteries are used in the model to estimate the GHG emissions.
  - The impact of changing the electricity grid on the life cycle emission of fuels and EV batteries is considered.

- The model can be translated into a decision support tool for the government and other stakeholders. Since the transport sector in India is expected to undergo a major transition, decision support such as this can contribute significantly to deciding policy interventions.

- The functions correlating multiple variables of the model are based on expected causal relations rather than a purely data-based approach. This allows the model to capture critical feedback effects. Moreover, the model has been parameterized using historical data.

- The model can evaluate the tailpipe emissions of different vehicle options. Thus, it can be used to study the impact of the adoption of different transport options on local/regional pollution. Moreover, the impact of adoption on other environmental impact categories can also be assessed using the model. This assessment is crucial to understanding the adverse effects of EV batteries.

System dynamics model development

SD model accepts complexity, nonlinearity, feedback loop structures, and delays that affect the system’s behaviour over time (Sterman 2000a). Thus, it uses quantitative means to investigate the dynamic behaviour of the system. The step-by-step procedure involved in the development of the system dynamics model is shown in Fig. 1. To develop an SD model, the first step is to develop a causal loop diagram (CLD) depicting the causal relationship between variables of the system. The causal relation between two variables can be either positive or negative. A causal loop is formed by connecting the causal relation of multiple variables in the form of a closed-loop, and it can be either positive (reinforcing) or negative (balancing) in nature. The CLD is the basis for developing the final quantitative model which brings out the dynamic behaviour of the system. The development of the quantitative model involves mainly two steps. First, the functional form connecting multiple variables needs to be identified. This can be based either on the nature of the underlying causal relationships, or data-based approaches such as regression. Second, the coefficients/parameters of the model need to be determined and this is generally done by using historical data, wherever available, and fitting the data to the proposed function. Additional details on SD modelling theory can be obtained from Sterman (2000b). This section describes the SD model developed in this work.

Scope and assumptions

The SD model developed in this work focuses on private transport vehicles in India, which includes cars and two-wheelers. The model does not consider public transport vehicles, such as buses, trains, or vehicles used to transport goods, because the adoption of new transport options, particularly EVs, will mainly be driven by private vehicles (Soman et al. 2020). The model considers five options for cars, namely, petrol, diesel, E85, CNG, and electric, and three options for two-wheelers, namely, petrol, E85, and electric. The total demand for cars and two-wheeler are the inputs to the model and depend on the population and economic prosperity that is captured using the per capita GDP values. The total vehicle demand is divided among the...
available options. The demand pattern, determined on an annual basis, decides the respective vehicle stock. The prediction of global price trends, such as those for crude oil and natural gas, is outside the scope of this work. Such trends are adapted directly from predictions given in literature. The life cycle greenhouse gas (GHG) emissions associated with each of the vehicle options are also included in the calculations. Following are the key assumptions used for developing the SD model:

- The number of vehicles and distance travelled per vehicle are inputs to the model and a function of population and per capita GDP.
- The purchase price and maintenance cost of each vehicle option, total vehicle life, and fuel efficiency of each vehicle are inputs to the model.
- Ownership cost is one of the major factors governing the purchase decision of various vehicle options. Additionally, there are other factors that affect the vehicle purchase decisions such as brand loyalty, technical performance, and environmental awareness. The apparent ownership cost considered here accounts for some of these factors through the incorporation of the inconvenience cost.
- Petrol, diesel, and ethanol prices depend on the fuel supply-demand dynamics considering the typical market dynamics.
- Ethanol production process from sugar and molasses has already matured and the production cost of ethanol from these sources does not reduce further.
- Electricity price is independent of electricity demand from the transport sector since the total electricity demand is dominated by other sectors.
- The model does not capture the impact of unpredictable events such as pandemic and regional conflicts, and their impacts on supply, demand, and prices.

The next section provides an overview of the causal loop diagram, and is followed by detailed explanation of the causal relations.

Causal loop diagram overview

The causal loop diagram (CLD) of the model (Fig. 2) is divided into five sections corresponding to each type of vehicle. Demand for cars and two-wheelers are input to the model. Demand for cars is divided among five options, i.e., petrol, diesel, E85, electric, and CNG. Demand for two-wheelers is divided among three options, i.e., petrol, E85, and electric. The new demand for each option alters the respective vehicle stock.

The division of demand among the available options is based on the ownership cost, with higher ownership cost reducing the annual demand (negative causal relationship). The vehicle selection model is explained in the next section. The ownership cost itself depends on several factors such as

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**Fig. 1** Steps involved in the development of the system dynamics model
the purchase cost of the vehicle, maintenance cost, and fuel cost. Purchase cost and maintenance cost are inputs to the model. Fuel price constitutes an important component of the ownership cost and can fluctuate with time. It is affected by the relative supply and demand of fuel in the market. Greater demand can lead to shortage of fuel, thereby leading to higher prices. Therefore, the model captures the causal relation between vehicle stock, fuel demand, fuel price, and ownership cost (all positive correlations). Thus, increased adoption of a type of vehicle can increase the corresponding fuel demand and thus the market price of that fuel. Since increased fuel price and the vehicle ownership cost has a negative effect on purchase probability, this constitutes a balancing loop in the model. This is true for both cars and two wheelers. For petrol and diesel, the price fluctuations also depend on the global fuel prices. Since modeling the global market is beyond the scope of this work, Brent crude oil price is taken as an input, and petrol and diesel prices are positively correlated with it.

For ethanol-based vehicles (cars and two wheelers), the fuel supply, demand, and price dynamics are again captured, while the purchase cost of the vehicle and maintenance cost are taken as input. The ethanol sector considers ethanol produced from molasses and lignocellulosic biomass, two sources that are expected to provide a major fraction of the total ethanol needed by the transport sector. Higher profits earned by each of these biorefineries lead to increased investment in the sector, and therefore, increased ethanol production (positive correlation). This increases the ethanol availability and reduces its price. Simultaneously, increased ethanol-based vehicle stock increases ethanol demand, causing the ethanol price to increase. The net change in the ethanol price, therefore, depends on the relative magnitude of these corrections. The production cost typically decreases with increasing production capacity. This cost reduction is attributed to greater experience as well as continued improvement in process technology, and is generally called the “learning effect”. Lignocellulosic ethanol is not yet economically feasible in India. However, it is expected that the cost of production will reduce in the coming years due to the aforementioned reasons. Therefore, the model relates the cumulative production from installed capacity to the production cost using a negative causal relation in CLD (Fig. 2). Thus, the loop connecting the capacity of ethanol production, production cost, and profit earned by biorefineries constitutes a reinforcing loop in the model. Similar to petrol and diesel prices, ethanol price determines the fuel expense of the vehicle, thereby changing its ownership cost.

For electric vehicles, electricity is the fuel. Since the demand for electricity by transport sector will be a small
fraction of the total electricity demand, it is assumed that electricity price is not affected by adoption of EVs. Thus, there is no fuel related feedback loop for EVs. Electricity price is a function of the electricity grid mix (US Energy Information Administration 2019) and the levelised cost of electricity (LCOE) from various sources (Pachouri et al. 2019). The gas driven vehicles can use CNG as well as CBG. CNG is used only if the CBG stock is not sufficient to meet the demand by gas driven vehicle stock. The price of CBG has been recommended by the Government of India through the SATAT scheme. Moreover, transport sector is a minor consumer of natural gas in India. Hence, price fluctuations through feedback is not modeled. The fuel price for gas driven vehicles is calculated as the weighted average of CBG and CNG prices depending on the consumption.

For EVs and CBG driven vehicle, lack of recharging/refueling infrastructure constitutes a major cause of inconvenience, which can reduce their adoption. The model captures this aspect in the form of an inconvenience cost that is added to the ownership cost of the vehicle. The required number of stations to recharge/refuel the vehicle without any delay is termed as the ideal number of charging stations for electric vehicles and the ideal number of gas refilling stations for CBG vehicles. The difference between the ideal and existing number of recharging/refueling stations is taken as the measure of inconvenience. As the respective vehicle stock increases, the ideal number of will also increase to cater to them, as shown by a positive dependence. In contrast, the inconvenience will reduce based on more availability of options (negative correlation). The improvement in charging technology for EVs, such as fast charging, will reduce the ideal number of charging stations as indicated by a negative dependence. The existing number of gas refilling stations is assumed to increase proportionately with the CBG production plants, to ensure sufficient gas outlets (positive dependence). If the ideal number of charging and gas refilling stations is greater than the existing number, there is an inconvenience in the adoption of EV and CNG vehicles, respectively. The higher the inconvenience, the lower will be the adoption of EV and CNG vehicles. Therefore, the inconvenience is converted into monetary terms and added to the ownership cost of the respective vehicles. Negative feedback loops have been identified connecting variables for respective vehicle stock, the ideal number of refueling stations, inconvenience cost, ownership cost of the vehicle, and demand for the vehicle.

The key outputs of the model are the annual demands/stocks of various vehicles, price trends for selected fuels, and GHG emissions from the private transport sector. This section provided an overview of the CLD. The next sections provide details pertaining to specific components of the causal loop diagram.

**Model formulation**

This section provides the detailed explanation of the different components of the CLD explained previously, and reports the functional forms used to capture the causal relationships.

**Vehicle demand**

The model requires the total number of vehicles as an input. The national population and per capita GDP have been shown to govern vehicle ownership as well as travel demand. Using this approach, the number of on-road vehicles each year is estimated. From the annual car and two-wheeler ownership, as well as the typical life of a vehicle, the annual demand for cars and two-wheelers is calculated. This demand includes new as well as replacement vehicles. When an owner purchases a vehicle for the first time, it is termed as a new vehicle. At the end of the service life of a vehicle, when the owner replaces it with another vehicle, it is termed as a replacement vehicle. The correlation of vehicle ownership and travel demand with GDP per capita can be represented through the Gompertz function, which captures a slow growth rate at low-income level, followed by faster growth that saturates at a value for higher income level (Dargay et al. 2007). The general form of the Gompertz function (Dargay et al. 2007) is given by Eq. 1:

\[
C = S \times e^{\mu x + \alpha}
\]

where, \(C\) is vehicle ownership per 1000 population, \(S\) is saturated vehicle ownership per 1000 population, \(\mu\) is GDP per capita, and \(\alpha\) and \(\beta\) are coefficients.

**Vehicle option selection**

The total demand for vehicles is divided among the available options based on the ownership costs. Even when using ownership cost as the decision-making factor, the selection is probabilistic due to the competition among various alternatives. The most expensive vehicle is still purchased by some due to factors such as performance and brand loyalty. Similarly, not everyone may prefer the cheapest option available. Moreover, reluctance to buy a new vehicle technology could either be due to inferior performance (such as mileage in E85 vehicle) or lack of necessary infrastructure (such as gas refilling stations for CNG and charging stations for electric vehicles). In summary, the vehicle purchase decision is probabilistic in nature. Therefore, this work uses the multinominal logit model.
(MNLM) reported in literature to capture these features (Lin and Greene 2010). An MNLM compares various attributes of different vehicle options and comes up with purchase probabilities. Here, we have used annual ownership cost as the governing factor. The equation to calculate the purchase probability of nth option is given by Eq. 2:

\[ P_n = \frac{e^{\frac{-OC_n}{\nu}}}{\sum_{m=1}^{m} e^{\frac{-OC_m}{\nu}}} \]  

(2)

where \( P_n \) is the purchase probability of nth option, OCn is the ownership cost of nth option and \( \nu \) is the scale parameter. Scale parameter gives the statistical dispersion of probability distribution. If the scale parameter is large, the distribution is more spread out. Vehicle specific data such as purchase price, annual maintenance cost, mileage, and cost trend of components such as batteries are needed to calculate the ownership cost. The inconvenience cost of CNG and electric vehicles due to lack of infrastructure is added to the ownership cost. Decisions driven by environmental consciousness are not considered in the first version of the model presented here.

**Petrol and diesel prices**

Two negative feedback loops connect petrol and diesel demands to their respective prices (Fig. 2). Ownership of petrol and E-85 vehicles increases the annual petrol demand. Similarly, diesel cars, heavy vehicles, and other industries increase the annual diesel demand. Petrol and diesel prices are positively correlated with their respective annual demands and Brent crude oil prices (Kumar et al. 2019). The equations used to capture the price fluctuations for petrol and diesel are:

\[ \frac{dP_i}{dt} = k_1 \times \frac{dC_i}{dt} + k_2 \times \frac{dD_i}{dt} \]  

(3)

\[ \frac{dD_i}{dt} = k_3 \times \frac{dC_i}{dt} + k_4 \times \frac{dD_i}{dt} \]  

(4)

where \( \frac{dP_i}{dt}, \frac{dC_i}{dt}, \) and \( \frac{dD_i}{dt} \) are changes in petrol, Brent crude oil, and diesel prices, respectively, compared to previous time step, \( \frac{dD_j}{dt} \) and \( \frac{dD_i}{dt} \) are changes in petrol and diesel demands, respectively, and \( k_1, k_2, k_3, \) and \( k_4 \) are model coefficients. The price change information, along with fuel prices in the previous time step, are used to calculate the fuel prices for a particular time step as follows:

\[ P_i = P_{i-1} + \frac{dP_i}{dt} \]  

(5)

\[ D'_i = D_i^{i-1} + \frac{dD_i}{dt} \]  

(6)

where \( P_i \) and \( D'_i \) are per unit petrol and diesel prices at time step \( i \). In practice, government taxes and subsidies will also affect the actual price paid by the consumers. However, those are difficult to predict. Hence, they are not explicitly considered. However, they are implicitly accounted for since historical data are used to fit the model as explained later. The model does not consider unpredictable changes in fuel prices such as the one in 2020 due to Covid-19 induced demand drop as well as that in 2021 due to a rapid surge in demand. Since the time horizon of interest in this work is much longer, it is argued that these short term shocks will not have significant effects on the long term trends.

**Ethanol supply, demand, and price**

The ethanol sector for transport in India is undergoing rapid changes in recent times. National Biofuel Policy 2018 permitted the use of sugar juice and food grain not suitable for human consumption for ethanol production in addition to molasses and lignocellulosic biomass. As a result, the ethanol production and blending rates have increased rapidly. The major fraction of the demand required to achieve 20% ethanol blending, however, is expected to be met by molasses and lignocellulosic residue. Hence, this model only considers these two sources for detailed modeling. The ethanol production from sugar and grains is considered an input to the model and is directly added to the total ethanol stock.

The production of ethanol either from molasses or lignocellulosic biomass is positively influenced by the profit earned by biorefineries as shown in Fig. 2. Since biorefineries require high capital investment and multiple years for erection and commissioning, the model has captured the time lag in the impact of profit/loss on the actual increase/decrease in ethanol production. Irrespective of feedstock as well as production technology used for ethanol production, the capacity adjustment will depend on the profit/loss in recent times. The autoregressive exogenous (ARX) model, a form of time series model, is used for fitting the equation relating ethanol production capacity from molasses and lignocellulosic biomass to the profit earned by these biorefineries with time delays. The equations are given as:

\[ EP_{m}^{i+k} = a_1 \times EP_{m}^{i} + b_1 \times P_{m}^{i} + b_2 \times P_{m}^{i-1} \]  

(7)

\[ EP_{b}^{i+l} = a_2 \times EP_{b}^{i} + b_3 \times P_{b}^{i} + b_4 \times P_{b}^{i-1} \]  

(8)

where \( EP_{m}^{i} \) and \( EP_{b}^{i} \) are the ethanol production capacities from molasses and lignocellulosic biomass in litres, respectively. \( P_{m}^{i} \) and \( P_{b}^{i} \) are the profits earned by molasses and
lignocellulosic biomass-based biorefineries, respectively. Model parameters include $a_1, a_2, b_1, b_2, b_3, k$, and $l$.

In literature, the experience curve is used to assess declining production costs as a result of increasing production (Axelsson et al. 2012). Learning gained in the production process to cost reduction is measured in terms of the “progress ratio” (PR). In the model, a learning curve with a particular PR has been assumed to calculate the production cost of ethanol.

Ethanol demand comes from E85 vehicles which run on 85% ethanol as well as mandatory 10% blending in petrol. If ethanol demand is lower/higher than ethanol supply, surplus/shortage of ethanol negatively influences the refinery gate price of ethanol (Fig. 2). The refinery gate price of ethanol is the price at which biorefineries sell ethanol to oil marketing companies (OMCs). In case of surplus availability, biorefinery gate price reduces to clear ethanol stock. If the price goes below the production cost of ethanol, the biorefineries incur losses and eventually reduce the production capacity. The impact is reversed in case of shortage, leading to profit and capacity enhancement. The calculation of refinery gate prices of ethanol is given by Eq. 9 and 10.

$$RP^i_m = TC^i_m - C_e \times ED^i$$  \hspace{1cm} (9)

$$RP^i_b = TC^i_b - C_e \times ED^i$$  \hspace{1cm} (10)

where $RP^i_m$ and $RP^i_b$ are per unit refinery gate prices of ethanol produced from molasses and lignocellulosic biomass, respectively. $TC^i_m$ and $TC^i_b$ are the production costs of ethanol from molasses and lignocellulosic biomass, respectively, $ED^i$ is the ethanol deficit (volume), and $C_e$ is the ethanol deficit coefficient. The same coefficient is used for both types of ethanol since the final product is the same. The consumer price of ethanol is determined as follows:

$$w^i_m = \frac{EP^i_m}{EP^i_m + EP^i_b}$$  \hspace{1cm} (11)

$$w^i_b = \frac{EP^i_b}{EP^i_m + EP^i_b}$$  \hspace{1cm} (12)

$$E^i = w^i_m \times RP^i_m + w^i_b \times RP^i_b + P$$  \hspace{1cm} (13)

where $w^i_m$ and $w^i_b$ are the weighted average ethanol produced from molasses and lignocellulosic biomass, respectively, $E^i$ is per unit ethanol price, and $P$ is the additional cost due to taxes, transportation cost, processing cost, and profit margin of OMCs.

**Electric vehicles and inconvenience costs**

The model considers the cost trends for EVs and batteries as inputs (see supporting document section S1). The vehicle and battery costs are assumed to reduce in the future with improved technology and designs. The model also considers the impact of insufficient charging stations and long charging time on adoption of EVs through an inconvenience cost. Inconvenience due to shortage of charging stations will be there for both electric cars and two-wheelers (Fig. 2) since charging stations will be shared between both. However, inconvenience due to long charging time will mainly affect four-wheelers since the charging times will be long due to larger battery capacities. The inconvenience cost due to insufficient charging stations is calculated by comparing the existing number of charging stations with the ideal requirement as follows:

$$I_{cs}^i = \max \left[ 0, \frac{(EV_{id}^{i+1} - EV_{id}^{i-1}) \times Scs}{EV_{id}^{i-1}} \right]$$  \hspace{1cm} (14)

where $I_{cs}^i$ is the inconvenience cost due to insufficient charging stations, $EV_{id}$, and $EV_{ac}$ are the ideal and existing number of charging stations, $Scs$ is the set up cost of a charging station, and $EV_{id}$ is the EV stock at time step $i$. The detailed calculation of the ideal number of charging stations is explained in supporting document section S2. The total inconvenience cost is divided among all EV users to get the per vehicle inconvenience cost. The second term in the MAX function calculates the inconvenience cost if the existing number of charging stations is lower than the ideal number of charging stations. This cost goes to zero if the existing and actual number of charging stations is the same. In case the existing number is more than the ideal number of charging stations, the model assumes that there is no additional benefit. The max function ensures that the inconvenience cost continues to be zero in such cases. The spatial non-uniformity in the distribution of charging stations across the country is not considered. The model assumes that a large fraction of EVs will be charged at public charging stations. The inconvenience cost will not be relevant if the EV owner can charge it at home. However, considering that cities in India have a large population living in apartments, where home charging may not be feasible, the fraction of people not using public charging would be low.

According to guidelines issued by the Indian government for charging infrastructure, a typical charging station will have three fast and two slow chargers. With improvement in charging technology, the charging time by both chargers will reduce (Nicola 2019). The inconvenience cost due to long charging time is the money required to be paid to save the additional time taken to charge an electric car by a
slow charger compared to a fast charger, and is calculated as follows:

\[ I_{ct}^i = \frac{(T_s^i - T_f^i) \times (S_c - S_f)}{E_{car}^{i-1}} \]  

(15)

where \( I_{ct}^i \) is the inconvenience cost due to long charging time in INR, \( T_s^i \) and \( T_f^i \) are time taken by slow and fast chargers in hour, respectively. \( S_c \) and \( S_f \) are the set up cost of slow and fast chargers, respectively, and \( E_{car} \) is the electric car stock at time step \( i \).

CNG vehicles and inconvenience cost

The current fraction of CNG-operated private vehicles in India is quite small. Moreover, CNG demand from the transport sector is met through liquified natural gas (LNG) imports. The SATAT scheme intends to promote the domestic production of compressed biogas (CBG). This will replace fossil CNG, thereby addressing the twin problems of import dependency and local pollution. The gap between the supply and demand of CNG as transport fuel as well as insufficient gas refilling stations are the biggest hurdles towards the adoption of CNG vehicles. The model considers the number of CBG plants set up through the SATAT scheme and their capacities as inputs contributing to the total CBG stock. Similar to the inconvenience cost calculation for EVs in "Electric vehicles and inconvenience costs", the model transforms the inconvenience due to insufficient gas refilling stations into monetary value and adds to the ownership cost of CNG vehicles.

The inconvenience cost due to insufficient gas refilling stations is calculated by comparing the existing number of gas refilling stations to the ideal number. The ideal number of gas refilling stations is the number that ensures unhindered refueling for a particular CNG vehicle stock. The existing number of gas refilling stations is proportional to the number of CBG plants as per the guidelines provided through the SATAT scheme. The detailed calculation of inconvenience cost is shown here:

\[ CNG_{id}^i = CNG_{id}^{i-1} \times s_{ratio} \]  

(16)

\[ CNG_{ac}^i = (CBG_{plants}^i - CNG_{id}^{i-1}) \times k_{perplant} + CNG_{id}^{i-1} \]  

(17)

\[ I_{cng}^i = \max \left[ 0, \left( \frac{(CNG_{id}^i - CNG_{ac}^i) \times S_{cng} \times CNG_{factor}}{CNG_{id}^{i-1}} \right) \right] \]  

(18)

where \( I_{cng}^i \) is the inconvenience cost due to lack of gas refilling stations in INR, \( CNG_{id}^i \) and \( CNG_{ac}^i \) are the ideal and existing number of gas refilling stations, \( S_{cng} \) is the set up cost of a gas refilling station in INR, \( CNG_{id}^i \) is the CNG vehicle stock, \( CBG_{plants}^i \) is CBG plants at time step \( i \) and \( s_{ratio}, k_{perplant} \) and \( CNG_{factor} \) are the parameters. Similar to the inconvenience cost calculation for EV (see Eq. 14), the second term of the MAX function in Eq. 18 calculates the inconvenience cost. If the existing number of gas refilling stations is more than the ideal number, no inconvenience is considered.

Model parameterization and scenario description

This section describes the model parameterization exercise for the model presented in the previous section. Vehicle specific data such as purchase price, maintenance cost, and mileage are given in Table 2 in Appendix. For the calculation of fuel expense of EVs, the predicted electricity price is given in supporting document section S3. Other details are explained later.

Vehicle ownership and travel demand

The vehicle stock data from 2001 to 2016 have been used to calculate \( \alpha \) and \( \beta \) in Eq. 1. The saturation numbers for car and two-wheeler ownership are 175 and 325 per 1000 population, respectively (Singh et al. 2020). For cars \( \alpha \) and \( \beta \) values are \(-5.38\) and \(-4.92 \times 10^{-4}\), respectively, while for two-wheeler, the values are \(-4.53\) and \(-8.52 \times 10^{-4}\), respectively. The comparison between historical and forecasted car and two-wheeler stocks is given in supporting document section S4.

The vehicle kilometer travelled (vkt) data for car and two-wheeler from 2000 to 2018 are fitted to estimate the parameters \( \gamma \) and \( \delta \) in Eq. 1. The saturation numbers of vkt for car and two-wheeler are 17091 km and 17107 km, respectively. For cars, \( \gamma \) and \( \delta \) are \(-0.82\) and \(-3.44 \times 10^{-4}\), respectively, while for two-wheeler the values are \(-0.58\) and \(-2.6 \times 10^{-4}\), respectively. The calculation of saturation numbers and comparison of historical and forecasted vkt are given in supporting document section S5 and S6, respectively.

Petrol and diesel prices

The prediction of Brent crude oil price is adopted from (US Energy Information Administration 2018). The coefficients in Eqs. 3 and 4 are estimated by minimizing the sum of square of error between actual and model predicted petrol and diesel prices between 2001 and 2018. The minimization is performed using the fminsearch solver in MATLAB®.
Since diesel is also consumed by sectors such as public transport, heavy vehicles and industries. Data between 2000 to 2019 show that this demand has been increasing approximately 5% every year, and hence it is assumed that the demand for these sectors continues to increase linearly at the same rate in future. The parameter values for petrol and diesel prices, i.e., $k_1$, $k_2$, $k_3$, and $k_4$ are 0.72, 1.17, 0.17, and 0.77, respectively.

Figure 3 shows that the proposed model fits the actual price fluctuations well with the $R^2$ value for petrol and diesel being 0.91 and 0.88, respectively. The model has over predicted petrol prices between 2008 and 2011. During this period, although the Brent crude oil price was high, Indian government subsidised petrol to protect consumers, resulting in lower price. The model also under predicts the price of diesel since it was subsidised by the government till 2014, thereby, reducing the impact of external factors like high demand or Brent crude oil prices.

**Ethanol production equation, progress ratio and price estimation**

The data for production capacity of ethanol and profit earned by molasses based biorefinery from 2013 to 2019 were available as these biorefineries are well established in India (USDA Foreign Agricultural Service 2019). However, lignocellulosic biomass-based biorefinery data for India were not available. Therefore, data for corn-based ethanol production in US (Moriarty et al. 2018) were used to estimate the model coefficients. The resulting coefficient values are reported in Table S9 in section S7 of supporting document. The difference in the coefficient values for molasses and lignocellulosic biomass-based biorefinery indicates that the molasses-based sectors responds more rapidly to profit. The comparison between the predicted and actual capacities of ethanol production from molasses and lignocellulosic biomass is given in supporting document in section S7.

The production cost of ethanol from molasses has been taken as 39 INR/lit (Punnathanam and Shastri 2020). Van den Wall Bake et al. (2009) reported a PR of 0.8 for sugarcane based ethanol. For corn-based ethanol, PR values of 0.87 (Hettinga et al. 2009), and 0.75 (Chen and Khanna 2012) has been reported. Therefore, this work assumes PR to be 0.85.

The coefficient for correlating ethanol price with the inventory $C$ in Eqs. 9 and 10 is estimated by using data of production capacity and profit earned by a corn-based ethanol plants in the US (Jayasinghe and Tang 2016). The coefficient value was estimated to be $-9.976 \times 10^{-4}$ INR/lit$^2$.

From historical data on refinery gate price of ethanol from sugarcane and ethanol price at which OMCs sold ethanol to consumers, the value of $P$ in Eq. 13 was found to be 60.24% of refinery gate price of ethanol.

**CBG price estimation and parameter values**

As mentioned previously CBG and CNG prices are an input to the model. The estimated CNG price is taken from the literature (Kumar et al. 2020). For CBG, the retail price of 55 INR/kg is considered and is derived from the price structure mentioned in the SATAT scheme document. This price is assumed to remain constant under SATAT scheme and is modified to account only for inflation.
The same approach resulted in the value of $s_{ratio}$ to be 260,000. For two-wheelers, $s_{ratio}$ was found to be 280,000. The numerical value of $CNG_{factor}$ was found to be 70.41.

Multinominal logit model

As mentioned previously, the multinominal logit model is a very important component of the SD model. $v$ values for car and two-wheelers are estimated using petrol and diesel vehicle sales data in 2019. For cars, the data indicated that 64% petrol and 36% diesel cars were sold in 2019, and this resulted in the value of $v$ to be 260,000. For two-wheelers, the same approach resulted in the value of $v$ to be 280,000.

GHG emissions

The GHG emissions considering here capture the complete fuel life cycle. The emission numbers included life cycle emissions (LCE) during the production and use of petrol, diesel, ethanol, CNG and CBG, emissions during the production of electricity as per the predicted grid configuration in India, and emissions during manufacturing, recycling, and discard of EV batteries (Table 3 in Appendix). The losses in the electricity distribution phase are also considered while calculating the total GHG emissions. GHG emissions during the combustion of ethanol and CBG are neglected because they are considered to be biogenic in nature. Sreekumar et al. (2020) had performed detailed life cycle assessment (LCA) of ethanol from rice straw using a process proposed to be commercialized. They found that 86% of the GHG emissions came from electricity used in the process. Additionally, detailed LCA study of India specific process for CBG production from biomass suggested that 74% of GHG emissions came from electricity (Munagala Meghana, personal communication). Therefore, the model accounts for the gradual shift in the electricity grid mix and its impact on the GHG emissions of electricity production and subsequently on ethanol and CBG production. Similarly, Accardo et al. (2021) had performed detailed LCA of NMC battery manufacturing and recycling processes. They have reported the life cycle inventory for electricity and natural gas required for manufacturing and recycling 1 kg battery pack. Based on that information, emission data from electricity grid and imported natural gas, the manufacturing and recycling emissions for 1 kg battery pack were corrected to obtain values in the Indian context.

Scenarios description

The model was programmed in MATLAB®. The simulation horizon was from 2020 to 2050 and the simulation time step was one year. The model has been used to simulate two different scenarios. The first scenario, termed as business-as-usual (BAU), assumes that current trends will continue in the future, with no adoption of the novel transport technologies. Although such a scenario is not realistic, it provides a benchmark to quantify the differences and benefits of adoption of new technologies. The second scenario, termed as the New Technology Adoption (NTA) scenario, assumes adoption of E85 vehicles, EVs, and CNG vehicles in the private vehicle stock along with 10% ethanol blending in petrol. For the NTA scenario, the charging infrastructure is assumed to develop at the rate of one charging station per 10,000 EVs. Additionally, it is assumed that E85 vehicles will be available for purchase from 2023 since such vehicles are not currently being sold in India. The rate at which CBG plants are set-up is based on the target of 5000 plants by 2025. A linear trend in setting up these plants is assumed and the trend is assumed to continue beyond 2025 as well. EV battery recycling rate is assumed to increase linearly from 1% in 2020 to 30% in 2050.

Sensitivity analysis

Since the NTA scenario results depend on a number of parameters that are not known with certainty, sensitivity analysis has been performed to identify key model parameters. This helps in identifying parameters that need to be estimated accurately as well as parameters that can be used as policy levers to achieve desired adoption trends. Sensitivity analysis was performed with respect to the price of electricity, production cost of lignocellulosic ethanol, rate of establishment of charging infrastructure, ethanol deficit
coefficient, purchase price of EV, growth rate of CBG plants, and cost of battery. The sensitivity analysis is performed one parameter at a time, and the ranges of uncertainty are explained in the subsequent sections.

Results and discussion

This section reports the results of various scenarios, sensitivity analysis, and policy experimentation and discusses its implications from climate change perspective.

Business-as-usual scenario

The simulation results for this scenario showed that the two-wheeler stock, as expected, comprised completely of petrol driven vehicles (Fig. 4). For cars, the results showed that petrol driven cars as always more preferred as compared to the diesel driven cars (Fig. 5). Due to the lack of any other vehicle options, the petrol and diesel demand increased rapidly with the consequent rise in the prices of both fuels (Fig. 6). Petrol price saturated at 292 INR/lit (14.73 $/gal) by 2050 due to saturation in vehicle demand. In contrast, diesel price continued to increase till 2050 (Fig. 6), because there were other uses for diesel and the saturation of those

![Adoption trend of various two-wheeler options in BAU and NTA scenarios](image1)

![Adoption trend of various car options in BAU and NTA scenarios](image2)
demands were not considered in the model. Diesel demand from private car stock was a smaller fraction of the total diesel demand, and hence its saturation did not affect the price profile. The total petrol and diesel consumption by private vehicle stock in 2050 was 270.6 billion litres, out of which, 140 billion litres, were for cars (54.07% as petrol share and the rest as diesel). Gomez Vilchez et al. (2013) had predicted the total petrol and diesel consumption from private car stock in India by 2050 to be 220 billion litres. Since BAU scenario also considered 10% mandatory blending of ethanol in petrol, the total petrol and diesel consumption by private car stock was lower than that estimated by Gomez Vilchez et al. (2013). The share of petrol consumption by passenger transport in 2050 was reported to be 43–58% by Paladugula et al. (2018), and the share predicted here was within that range.

The total GHG emissions from private vehicle stock in 2050 were 898.76 million tonnes CO$_2$e, which included 713 million tonnes CO$_2$e of tailpipe emissions and rest coming from production of petrol and diesel. Out of the total emissions, the private car stock contributed 450.5 million tonnes CO$_2$e, while the rest was contributed by two-wheeler stock. The tailpipe GHG emissions were close to the range given by Paladugula et al. (2018) and Shukla and Dhar (2016). Gomez Vilchez et al. (2013) have predicted the GHG emissions from private car stock in 2050 to be 550 million tonnes CO$_2$e, which was higher than the value predicted here, possibly due to the consideration of mandatory 10% blending in this work. Paladugula et al. (2018) have reported 4.1–6.1% annual growth in CO$_2$e emissions from transport sector from 2010 to 2050 which is consistent with the average annual growth of 4.73% found in this study. The petrol and diesel share in total GHG emissions from private vehicle stock were 76.3% and 23.7%, respectively. Although the emission during production and combustion of diesel was higher than petrol (Table 3 in A), greater petrol vehicle stock led to much bigger contribution of petrol related GHG emissions. India’s GHG emissions by 2030 should be within 3.8–3.9 billion tonnes CO$_2$e in order to meet the Paris Agreement target (Energyworldcom 2018). Considering that 10% of the total emissions would be caused by transport sector out of which 87% would be due to road transport (Paladugula et al. 2018), the GHG emissions from road transport should be 339 million tonnes CO$_2$e to meet the target level. However, simulation results showed that the total GHG emissions from private vehicle stock in 2030 were found to be 502.36 million tonnes CO$_2$e. Thus, in the absence of novel transport options, private vehicle stock in 2030 would be emitting almost twice the emissions from entire transport sector in 2016.

**New technology adoption scenario**

For the NTA scenario, simulation results (Figs. 4 and 5) showed that petrol driven vehicles continued to be the most preferred option for both two-wheelers and cars. However, there was a significant reduction in the petrol vehicle stock due to the availability of adoption of other options. The cumulative adoption of E85, EVs, and CNG in private vehicle stock was 34% in 2050. Petrol, E85, EVs, diesel, and CNG vehicle share in total vehicle stock in 2050 were 59%, 20%, 8.8%, 7.2% and 5%, respectively. Share of electric car
and two-wheeler in new sale in 2030 were 18.5% and 13.4%, respectively, which was less than the target of 30% share proposed by the government. The adoption of E85 started later than EV due to non-availability assumption. However, E85 vehicles were adopted at a faster rate, thereby overtaking the total stock. The faster adoption of E85 vehicles was due to higher ownership cost of EV. Even though a growth rate for number of charging stations and a decreasing time profile for charging EV was considered, the inconvenience cost along with higher purchase price of EV made it an expensive option. In case of CNG cars, some fluctuations were observed in the adoption rate till 2030 and afterwards it increased steadily. These fluctuations arose due to negative feedback loop connecting the ideal and actual gas refilling stations to inconvenience, and thereby to the ownership cost as well as demand for CNG cars (Fig. 2).

In 2030, petrol and E85 vehicle contributed 70% and 16.12%, respectively, to the total vehicle stock. However, the blending rate was found to be still quite low at 8.8%, much lower than 20% targeted by the government. The blending rate in 2021 is about 8%, and therefore, this was a surprising observation. As mentioned previously, the recent rapid rise in blending rate has been due to use of sugar and molasses as feedstock. The ethanol production from molasses, sugarcane juice, and damaged food gains were assumed to saturate before 2030, while ethanol production from lignocellulosic biomass would increase gradually as per the profit earned by biorefinery (Eqs. 7 and 8). Since the lignocellulosic ethanol production took time to ramp up, the targeted blending rate of 20% could not be achieved. Comparison of government’s target regarding ethanol blending and EV adoption with the simulated results are shown in Fig. 7a.

The total consumption of petrol and diesel by private vehicle stock in 2050 was 159.5 billion litres, which was 41% less than that in the BAU scenario. Petrol and diesel consumption from private car stock was 73.3 billion litres, while rest was from two-wheeler stock. Availability of alternate options and the reduced stress on petrol demand resulted in a lower saturation price of 198 INR/lit (10.7 $/gal) for petrol in 2050 (Fig. 6). This value of course accounted for the price balancing loop incorporated in the model. The adoption of alternatives also reduced diesel consumption, and therefore, the diesel price, as compared to the BAU scenario. However, the reduction was not significant since, diesel demand from private cars was not a major fraction of the total diesel consumption.

The adoption of E85 vehicles, EVs, and CNG vehicles reduced the total GHG emissions from private vehicle stock in 2050 to 668.75 million tonnes CO$_2$e, which were 25.6% lower than those for the BAU scenario. The total emissions included 405.4 million tonnes CO$_2$e of tailpipe emissions while the rest being indirect emissions from the fuel and battery production as well as battery recycling steps. The share of GHG emissions by petrol, diesel, E85, electric, and CNG private vehicle stock in 2050 were 43.65%, 12.37%, 12.2%, 3%, and 3.2%, respectively. The emissions from diesel were higher than E85, even with lower vehicle stock since diesel production and combustion was more carbon intensive. The GHG emissions from private vehicle stock in 2030 were 461.25 million tonnes CO$_2$e, which were again higher than the targeted GHG emissions of 339 million tonnes CO$_2$e in order to achieve Paris Agreement target as shown in Fig. 7b. The reported results of BAU and NTA scenarios in this section are also presented in the form of comparison for easier interpretation in Table 1.

The results reported previously assumed the life cycle GHG impact of 2.72 kg CO$_2$e per liter of ethanol as calculated by Sreekumar et al. (2020). Sreekumar et al. (2020) have also proposed opportunities to reduce the impact significantly. Additionally, they have also summarized results of other LCA studies of ethanol production in the Indian context. Due to differences in feedstock as well as conversion technologies, the life cycle GHG emissions per liter of ethanol differ. Based on the emission reduction options proposed by Sreekumar et al. (2020) and values reported in other studies, an average value of 1 kg CO$_2$e per liter of ethanol was considered. For this value, the GHG emissions of the transport sector reduced to 625.4 million tonnes CO$_2$e, a 6.5% reduction as compared to the previous result.

| Table 1 Comparison of BAU and NTA scenarios |
|---------------------------------------------|
| Variables | BAU scenario | NTA scenario |
| Petrol consumption in car stock in 2050 (in billion litres) | 75.7 | 39.68 |
| Petrol consumption in two-wheeler stock in 2050 (in billion litres) | 130.6 | 86.2 |
| Diesel consumption in car stock in 2050 (in billion litres) | 64.3 | 33.62 |
| Cumulative adoption of new vehicle options in 2050 | 0 | 34% |
| Total GHG emissions in 2030 (in Mt CO$_2$e) | 502.36 | 461.25 |
| Total GHG emissions in 2050 (in Mt CO$_2$e) | 898.76 | 668.75 |
| Tailpipe GHG emissions in 2050 (in Mt CO$_2$e) | 713 | 405.4 |
| Indirect emissions in 2050 (in Mt CO$_2$e) | 185.76 | 263.35 |
Effect of carbon tax

Under imposition of carbon tax, the ownership cost of the vehicle increases based on the life cycle GHG emissions during the vehicle and fuel use. Therefore, it is believed that high carbon tax would push the vehicle owners to switch to lower carbon intensive vehicle options such as E85, EVs, and CNG vehicles. The effect of carbon tax on adoption of E85, EVs, and CNG vehicles can be seen in Fig. 8. It can be observed that as carbon tax rate

Fig. 7 Comparison of government targets and model predictions for different indicators. (a) Comparison of Government of India targets for electric cars, electric two wheelers, and ethanol blending rates with model predictions. Government targets are assigned value of 100, while model predictions are calculated relative to that. (b) Comparison of GHG emission (in Mt CO2e) in BAU and NTA scenarios with the 2030 INDC target.
increased from 0 to 10 INR/kg CO$_2$e, the share of E85, EVs, and CNG vehicles increased in total vehicle stock. Consequently, with increase in share of E85, EVs, and CNG vehicles, the GHG emissions reduced. The GHG emissions in 2030 under no carbon tax rate were 461.25 million tonnes CO$_2$e, which reduced to 442.51 million tonnes CO$_2$e as carbon tax rate increased to 10 INR/kg CO$_2$e. The government’s targets of 20% ethanol blending in petrol by 2025 as well as 30% EV sales in new sales by 2030 were assessed under different carbon tax rate scenarios. It was found that imposing carbon tax increased the ethanol blend rate in 2025 from 8.7% under no carbon tax scenario to 11.6% at carbon tax rate of 10 INR/kg CO$_2$e. However, ethanol blend rate was found to be lower than the 20% target in 2025 by the government. Similarly, carbon tax also increased the electric car and two-wheeler adoptions from 18.51% and 13.4%, respectively, in 2030 under no carbon tax rate, to 22.6% and 53.85%.

![Fig. 8 Effect of carbon tax rate on adoption of E85, CNG, and electric vehicles](image)

![Fig. 9 Impact of model parameter values on adoption of EVs and E85 vehicles in year 2050. The change in adoption is shown with respect to the adoption for the base case. Change in E85 adoption is considered to demonstrate sensitivity with respect to production cost of lignocellulosic ethanol and ethanol deficit coefficient. Change in EV adoption is considered to demonstrate sensitivity with respect to, purchase price of EV, battery cost, electricity cost, and number of charging stations](image)
respectively, in 2030, at carbon tax rate of 10 INR/kg CO$_2$e. However, 30% electric car sales in new sales in 2030 couldn’t be achieved. These simulations indicated that carbon tax on its own would not be a sufficient to achieve the desired targets.

**Sensitivity analysis**

Figure 9 shows the sensitivity of adoption of either EVs or E85 vehicles with respect to model parameters. The parameters mentioned previously were varied from $-40$ to $40\%$ from base value for the analysis. Among EV specific parameters, purchase price of EV had the greatest impact on adoption rate, followed by cost of battery, cost of electricity, and the number of charging stations. The purchase price of an EV constituted on an average $54\%$ of the total ownership cost of the vehicle, followed by $29\%$ for battery replacement cost and $17\%$ for maintenance cost. Therefore, it was expected that reduction in the purchase cost of EV would have the greatest impact on pushing the adoption.

Variation in ethanol production related parameters, namely, production cost of lignocellulosic ethanol and ethanol deficit coefficient, did not have a major impact on the adoption of E85 vehicles. When the ethanol production cost increased by $40\%$, there was greater negative impact on the adoption of E85 vehicles. This happened because it took longer to achieve the saturation cost of 45 INR/lit (2.3 $/gal$), and consequently, the adoption was negatively affected. Reduction in ethanol deficit coefficient made the refinery gate price of ethanol less sensitive to deficit (Eqs. 9 and 10). Refinery gate price of ethanol was the major part of the consumer ethanol price, and hence reduction in ethanol deficit coefficient reduced the fuel expense of E85 vehicles, thereby increasing its adoption.

The CBG plants were assumed to be installed as per the SATAT scheme target, and base case assumed that the same rate of installation would continue beyond 2025. In order to assess the sensitivity of this assumption, three different growth rates for CBG plants installation were considered (Fig. 10a). Corresponding to growth of CBG plants, gas refilling stations were also increased proportionately. It was found that under high growth rate scenario, the adoption of CNG cars increased so rapidly that CNG car stock became the second highest after petrol car stock in 2050 (Fig. 10b). Additionally, GHG emissions in 2030 also reduced by $3.7\%$ from the NTA scenario to 454.2 million tonnes CO$_2$e. As expected, low growth rate reduce the adoption rate of CNG vehicles. Increase in CNG vehicle adoption was compensated by reduction in adoption of other vehicle options, and as a consequence, the fuel pricing and the production sector were affected. The additional CNG vehicles in high growth rate scenario mostly replaced E85 vehicles (Fig. 10b). This had cascading effects on the biomass-based ethanol production capacity, which reduced by 253 million litres. To further examine the impact of high adoption of EV and CNG vehicles in the transport sector, the high growth rate scenario was modified to include more number of charging stations that assumed in NTA scenario. The assumption of 1 charging station per 10,000 EV stock was changed to 1 charging station per 100 EVs in the model. The results showed that biomass-based ethanol production capacity and ethanol price reduced by 818 million litres and 2 INR/lit, respectively, compared to NTA scenario.

**Impact of battery recycling and discard**

Presently, EV battery recycling has not been established much in India. However, it is expected that with increase in EV adoption, battery recycling would become a necessity in order to avoid large stock of discarded batteries and their associated environmental impacts. In this regards, the impact of changes in battery recycling rates on GHG emissions was quantified. The NTA scenario was modified to compare the impact of $100\%$ recycling rate to $100\%$ discard rate of EV batteries by 2050. $100\%$ recycling rate implied that all the EV batteries will be recycled at the end of their service life, while $100\%$ discard rate meant that all batteries will be discarded. The results showed that GHG emissions for no recycling ($100\%$ discarding) were 461.3 million tonnes CO$_2$e, while for $100\%$ recycle, emission were 460.83 million tonnes CO$_2$e. It is evident from the results that the difference in impact was not significant for GHG emissions. However, the impacts would be significant for other impact categories which considers leaching of harmful chemicals in soil and water. Such impact categories are human toxicity potential, freshwater ecotoxicity potential, and eutrophication potential. Simulation results showed that human toxicity potential in thousand tonne 1,4-DB eq. for $100\%$ recycling and $100\%$ discard scenarios in 2050 were 327 and 1448.2, respectively. Similarly, freshwater marine ecotoxicity potential in thousand tonne 1,4-DB eq. for $100\%$ recycling and $100\%$ discard scenarios in 2050 were 594 and 7906.3, respectively.

**Conclusion**

The objective of this work was to develop a system dynamics model to study the adoption of novel transport options, namely, E85, EVs, and CNG vehicles, in the Indian private transport sector. The model captured the effect of supply-demand dynamics for each transport option and fuel, and also incorporated aspects of inconvenience for EVs and CNG vehicles. The simulation results indicated that given the current and expected technology and policy combinations, the targets proposed by the Indian governments could not be achieved. Both EV adoption and ethanol blending
Fig. 10 Number of CBG plants and stock of various options in car in 2050 under high, medium, low growth rate and NTA scenarios are presented in (a) and (b), respectively. High, medium, and low growth rate scenarios assume 50,000, 20,000, and 10,000 CBG plants to be installed by 2050, respectively, and a linear growth in number of CBG plants between 2025 and 2050.
fraction were much lower than the targeted values. Although introduction of novel options reduced the overall GHG emissions, it still was not enough to achieve the reduction targets as per India’s INCD as part of the Paris Agreement. This indicated that the targets set by the government are too ambitious. The sensitivity analysis indicated that purchase price of EVs and the lack of charging infrastructure were the biggest hurdles in greater adoption of EVs. Therefore, the government must explore options such as purchase subsidies to promote EVs. The model identified 25% reduction in the purchase price was required, and additional policy actions like discount in cost of electricity and carbon tax were needed to achieve EV adoption targets. Similar to the case of EVs, adoption of CNG vehicles was also hindered by insufficient CBG supply and gas refilling stations. The simulation results suggested that growth rate of CBG plants and gas refilling stations should be greater than the rate adopted under SATAT scheme in order to have significant adoption of CNG vehicles. From GHG emission reduction standpoint, improvements in battery production technology, ethanol production process from lignocellulosic biomass, and CBG production from biomass were identified as key requirements. The model can be used to test several additional scenarios and possibilities to gain a quantitative understanding of adoption trends and sectoral GHG emissions. From that standpoint, the SD model is as important an outcome of this work as the results presented here.

It is also important to acknowledge the limitations of this model. Firstly, it is acknowledged that the model, similar to other SD models, is based on several assumptions driven either by the unavailability of data or the desire to reduce the model complexity. These assumptions have been mentioned in the model description. Consequently, the results should not be viewed as predictions but rather as one of the numerous future possibilities. Secondly, the transport sector in India is expected to undergo several changes, and some of those could be disruptive. Therefore, the model will need to be updated periodically to capture these changes. Thirdly, the model will also need to be re-parameterized as more data become available. Therefore, this contribution should be viewed as a foundation towards a more comprehensive framework.

With this broader vision, work in the immediate future will address some of the assumptions in the current model. One important assumption is that vehicle purchase decisions are based solely on the apparent cost of ownership. In practice, these decisions are also impacted by other factors, some of which are difficult to quantify. Therefore, work is being done currently to extend the vehicle selection model to include factors beyond economics (ownership cost). In particular, relative preference for economics and environmental performance by individuals in a probabilistic framework is being considered. Moreover, the model is also currently being extended to consider environmental impacts beyond GHG emissions, such as emissions of oxides of sulphur and nitrogen, particulate matter, and black carbon. This is particularly useful to evaluate the impacts of EV battery disposal into the environment. Furthermore, for a broader sustainability-based assessment of this work, other benefits of the adoption of E85, CNG, and electric vehicles, include the utilization of lignocellulosic waste generated in farms, sustainable municipal solid waste management, prevention of agricultural residue burning, zero tailpipe emission in EVs and the consequent improvement in urban air quality would be considered.

Appendix

Model inputs

Vehicle purchase price, maintenance cost, and performance data has been reported in Table 2. Note that the purchase price and maintenance cost of petrol and diesel cars are based on average price of models available in the market today and also based on (cardekho.com 2016). The purchase price of TVS Apache RTR 200 ethanol-based two-wheeler is 11,000 INR more than comparable petrol variant. Based on this the E85 car and two-wheeler purchase prices are 10,000 INR more than petrol vehicles, also the annual maintenance cost and service life of E85 vehicles are taken within the range of petrol and diesel vehicles, because only minor changes in engine design are needed to accommodate ethanol. On comparing the mileages of these variant, it was found that petrol variant has higher mileage by 16% compared to ethanol variant. On the basis of this the E85 car and
two-wheeler mileages are calculated. Purchase price, mileage, and battery capacity of electric car and two-wheeler has been taken from TATA Nexon EV and TVS iQube model, respectively. Because EV is new technology service life of vehicle is not specified, but it is assumed service life of EV will be within the range of petrol vehicle as EV does not have mechanical moving parts which deteriorates the vehicle over usage. Emission data for various fuels are shown in Table 3. Life cycle emission data for petrol, diesel, and electricity production from coal, solar, wind, natural gas, hydro, and nuclear are calculated from openLCA software. Data related to ethanol yield from molasses and biomass, and charging infrastructure are listed in Table 4 in Appendix.
Table 3 Life cycle and combustion emission of various fuels

| Parameters                                      | Values                        |
|------------------------------------------------|-------------------------------|
| Life cycle emission (LCE) of petrol (kg CO₂e/lit) | 3.133 (Wang et al. 2016)      |
| LCE of diesel (kg CO₂e/lit)                     | 3.32 (Wang et al. 2016)       |
| LCE of ethanol production (kg CO₂e/lit)         | 2.82 (Sreekumar et al. 2020)  |
| LCE of electricity from coal (kg CO₂e/kWh)      | 1.708 (Ecoinvent database v3.3) |
| LCE of electricity from solar (kg CO₂e/kWh)     | 0.049 (Ecoinvent database v3.3) |
| LCE of electricity from wind (kg CO₂e/kWh)      | 0.033 (Ecoinvent database v3.3) |
| LCE of electricity from hydro (kg CO₂e/kWh)     | 0.004 (Ecoinvent database v3.3) |
| LCE of electricity from nuclear (kg CO₂e/kWh)   | 0.014 (Ecoinvent database v3.3) |
| LCE of electricity from natural gas (kg CO₂e/kWh)| 0.692 (Ecoinvent database v3.3) |
| LCE from battery manufacturing (kg CO₂e/kWh)    | 157.75 (Accardo et al. 2021)  |
| LCE from battery recycling (kg CO₂e/kWh)        | 54.9 (Accardo et al. 2021)    |
| LCE of imported CNG (kg CO₂e/kg)                | 0.0027 (Kumar et al. 2020)    |
| LCE of CBG (kg CO₂e/kg)                         | 3.56 (Munagala Meghana personal communication) |

Table 4 Data related to ethanol production and charging infrastructure

| Parameters                                      | Values                        |
|------------------------------------------------|-------------------------------|
| Sugarcane yield (in tonnes/hectare)            | 82 (Purohit and Dhar 2015)    |
| Molasses yield from sugarcane (ton molasses/ton sugarcane) | 0.045 (Purohit and Dhar 2015) |
| Ethanol yield from molasses (lit/ton molasses) | 240 (Soam et al. 2015)        |
| Ethanol yield from biomass (lit/ton biomass)   | 253 (Dhanraj et al. 2021)     |
| Initial production cost of lignocellulosic ethanol (in INR/lit) | 70 (Punnathanam and Shastri 2020) |
| Saturation production cost of lignocellulosic ethanol (in INR/lit) | 45 (Punnathanam and Shastri 2020) |
| Number of fast chargers in charging station   | 3 (Shah 2019)                 |
| Number of slow chargers in charging station   | 2 (Shah 2019)                 |
| Setup cost of fast charger (INR)               | 15,70,000 (Shah 2019)         |
| Setup cost of slow charger (INR)               | 2,15,000 (Shah 2019)          |
| Setup cost of charging station (INR)           | 40,00,000 (Shah 2019)         |
| Setup cost of gas refilling station (INR)      | 75,00,000 (hrexorg 2021)      |
| Inflation rate                                 | 3.5 (Reserve Bank of India)   |

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Data availability All the used data are provided as part of the appendix, supplementary information or are publicly available.

Declarations

Conflicts of interest The authors have not disclosed any competing interests.

Code availability Codes are not provided.

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