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The Transportation Leapfrog: Using Smart Phones to Collect Driving Data and Model Fuel Economy in India

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ABSTRACT
Car ownership in India is expected to skyrocket in the coming decades, strongly driven by rising incomes. This phenomenon provides unprecedented opportunities for automakers and equally unprecedented social and environmental challenges. Policymakers, urban planners and civil society see this car boom leading to an explosion in problems related to congestion, infrastructure, air pollution, safety, higher oil imports and climate change. For all these stakeholders to take effective action, good data on how people use their cars, their demand for mobility and their behavior in mobility is essential. Unfortunately, there is very little data on the Indian transport sector as a whole and virtually none on real-world vehicle performance and use. The rapid development of high quality mobile telecommunications infrastructure provides India with the opportunity to leapfrog the West in cheaply collecting vast amounts of useful data from transportation. In this paper, we describe a pilot project in which we use commercial smart phone apps to collect per second car driving data from the city of Pune, instantly upload it through 3G and prepare it for analysis using advanced noise filtering algorithms for less than $1 per day per car. We then use our data in an Autonomie simulation to show that India's currently planned fuel economy test procedures will result in over-estimates of fuel economy of approximately 35% for a typical Indian car when it is operated in real world conditions. Supporting better driving cycle development is just one of many applications for smart phone derived data in Indian transportation.

INTRODUCTION

Car ownership in India is expected to skyrocket in the next two decades (1). India is projected to become the world's third largest auto market after the US and China by 2030 and possibly overtake the US by 2035 (2). Most importantly, this demand is primarily due to rising incomes and cannot be easily averted through aggressive Avoid-Shift (A-S) policies because car ownership is dictated by more than a simple desire for convenient mobility (3). Automakers recognize the huge emerging market both in India and China and are gearing up to supply them. However, if the car ownership projections come true, India alone will be responsible for almost 8% of global transportation greenhouse gas emissions by 2030 (4, 5) and will need to import more than 85% of its crude oil (1). In addition, India already has the highest annual road accident deaths in the world (6), some of the world's worst air pollution from transport, and severely underdeveloped transport infrastructure (7). Thus, the social and environmental externalities from this car boom need to be aggressively and cost-effectively mitigated starting immediately. To design effective measures policymakers, academics, urban planners and civil society need excellent data from Indian transportation. Unfortunately, there is very little macro data on the Indian transport sector (8) and virtually no useful data on mobility behavior and demand (4, 9).

The traditional approach to transport data collection follows a hardware intensive approach with installation of on-road sensors, laser and vehicle monitors, specialized in-vehicle loggers, etc. Developed nations such as the U.S. have invested tens of billions of dollars in such data collection infrastructure for transportation (10). Current hardware approaches are very expensive. In the US, each traffic monitoring device to be used on a single intersection costs between $2,000 (for a simple loop traffic counter) and $24,000 (for machine vision), plus installation costs and $2,000-$4,000/year for maintenance (11). These costs do not include the installation and maintenance of a data management system. India had approximately two million kilometers (km) of paved roads in 2008, according to the World Bank (12). If just 20% of these kilometers were monitored for simple vehicle speeds and counts, the hardware costs would rise to $4 Billion (assuming an average of $10,000/device and one device per km).

India does not have the time, or the capital resources, to follow such a hard path that collects only rudimentary information. Fortunately, the extremely rapid development of India's mobile telecommunications infrastructure provides us with the opportunity to get even better transportation data than traditional approaches at much lower costs. Several states within the U.S. have found that the costs of using vehicle probes (dedicated vehicles, usually commercial, with installed speed monitoring equipment) are about one-fifth to one-fourth that of dedicated hardware. In this paper, we describe an innovative transport data collection framework that is cheaper and able to gather more data than the probe vehicle approach. Our approach piggybacks on the great Indian telecommunications leapfrog (13, 14), to catalyze an equally significant leapfrog in transportation data acquisition and analysis. Specifically, we describe the technical and economic details of a pilot project in which we use commercially available smart phone apps to collect per second data on speed, acceleration, GPS location and inclines for cars in the city of Pune that is instantly uploaded by 3G and then prepared for analysis using advanced noise filtering algorithms.

The data we collect has numerous applications that range from systems engineering design of automobiles to urban transportation planning and management. In this paper, we choose to highlight an application that can substantially improve the labeling test procedure for India's proposed passenger car fuel economy standards (15). We use our speed-time driving profiles from Pune, a large Indian city representative of traffic and infrastructure conditions where most of India's passenger car miles will be logged over the next two decades, and compare it with the Modified Indian Driving Cycle (MIDC), the currently designated test cycle that is not based on actual Indian driving data, but instead is a lightly modified European drive cycle (16). We find that the smart phone derived real world driving profiles, which cover both urban and suburban trips, on average show substantially sharper and more frequent acceleration and braking in addition to much longer idling times. In order to demonstrate the implications of this for the fuel economy labels, we simulate the performance of a low-powered compact model most representative of models that will dominate future Indian sales, in Autonomie, a widely used powertrain simulation program. We find that the current test procedures could overstate fuel economy values by approximately 35% relative to real world performance. India chose to use the MIDC, which is derived from the New European Driving Cycle, for reasons that are not entirely clear. We surmise that the development cost must have been a factor. Regardless of the historical reasons for the choice of the MIDC, we show that by employing smart phone based driving cycle development techniques, India can develop a much more appropriate test cycle cheaply.

In addition to the specific policy application we highlight in this paper, the uses of vehicle specific smart phone based data can support a wide range of critical transportation planning, engineering and policy decisions. Some examples include the use of smart phone derived data to:

- Employ a systems-based, bottom-up engineering design of automobiles for Indian traffic, consumer preferences and the regulatory environment.
- Develop a multi-modal, multi-sectoral transport energy demand and emissions model for India.
- Plan public transportation infrastructure based on mobility demand in key corridors.
- Plan highway and road infrastructure.

In our research group at UC Berkeley and Lawrence Berkeley National Laboratory we plan to use our innovative data collection and analysis techniques for several similar applications. We also note that the same key factors hold true in much of the rest of the developing world - poor transportation data along with excellent, affordable mobile telecommunications infrastructure. Hence, the techniques we highlight here can be deployed to solve transportation problems in other major emerging regions like China, Latin America, Southeast Asia and Africa.

METHODS

Smart Phone Data Collection

Our smart phone derived data collection approach can be used in a variety of contexts for a variety of applications. We can collect speed, location and acceleration data for an individual person across all modes that he or she uses in a given time period. Smart phone derived data collection for transportation has become increasingly popular. Much recent work has focused on using the smart phone to both collect data, and deliver feedback to an individual. Specific examples include modeling vehicle electrification impact for individuals (17), feedback to show the cost and carbon benefits of transit ridership (18), and the replacement of in-vehicle navigation systems with smart phones (19).

In addition, other researchers have used smart phone based data collection to support better understanding and management of transportation systems. Recent examples include using cell signals to monitor the timeliness of transit (20), using a fleet of smart phone probes to monitor real-time traffic conditions (21), planning bike routes (22), and using smart phone-based approaches to enhance or displace household travel surveys (23, 24).

Our methodology for data collection most closely resembles that of Charlton and Schewel in that we utilized commercial smart phones with dedicated data-collection apps, and analyzed the movements of distinct devices (as opposed to groups of devices like Herrera and Thiagarajan). Unlike the travel survey work, we did not supplement smart phone data collection with surveys for the participants. Finally, as explained below, the applications we describe in this paper do not need locational data, though the app is capable of collecting it. Our app is also capable of harvesting all the data gathered by the vehicle's onboard computer.

For this pilot study, we selected three participants in Pune, each with a slightly different mix of urban and highway routes in their daily car commute, who already owned their smart phones. We asked each participant to install an existing Android app (specifically, Google MyTracks) (25). Each phone was configured for one second trip data collection of time stamp, speed, altitude, and accuracy sensitivity. At the start of each trip, the participant turned on the app and initiated recording. The app recorded trip data every second and uploaded to our server in Berkeley, CA every time 3G connectivity was available. When the trip was complete, the participant stopped the recording. We recorded five morning and evening commute trips by each participant, totaling over 350 km of travel.

TABLE 1 shows the breakdown of data collection costs in the pilot project and compares those with the costs of using a dedicated hardware approach. If the cost of purchasing the phone is excluded since our participants already owned one, the overall cost of collecting the data for one month was less than \$1.00 per vehicle per day, without including research labor. Even if we had to purchase a smart phone just for this effort, the total cost of just using that to collect trip data would still less than \$5/day, much lower than using a specialized, in-vehicle data logger, which costs between \$200 and \$1000 for vehicles in the US, plus a unique monthly data subscription (26, 27). The phone we priced is the Samsung Galaxy Y S5360 (28), which is almost twice the price of the cheapest Android on the Indian market. However, the Galaxy Y S5360 is the most affordable Android on the Indian market with a GPS, accelerometer and battery life of the necessary quality and reliability for our work.

TABLE 1 Data Collection Costs in Pilot Project. These figures exclude server costs and set up/processing engineer costs which would be comparable for the two data collection approaches

Cost Component	Pilot Study Cost (US$)	Cost of Traditional Dedicated Hardware Approach (US$)
Cost of Phone/GPS device	$140 OR $0 if leveraging existing phones	$600
Cost of 3G Data plan/month	$4.5 for dedicated plan OR Less than one percent of one cent per day if data plan already exists and new geo data is incremental	~$18/month
App cost	$1.99	$0
Total Cost for one month of data collection for one user	Between $2 and $150	$620

Sources: (27-29)

The benefits of our method were the low cost, the ease of installation, and the high accuracy and time rating of the data. The main detriment was the fact that test subjects often forgot to trigger the app to start recording information at the start of each trip (and stop at the end of trips). In order to mitigate this, which would be necessary to use this scheme a large scale, we are developing a specialized app that turns on automatically during travel (either by sensing movement or by permanent installation in the car, connected to the power source, and recording whenever the car is turned on).

It is important to note that this pilot project was undertaken with minimum funding to demonstrate the low cost, feasibility and overall ease of smart phone based transport data collection in a developing country where there are no other means of obtaining such data. Further, we collected our data without any need for expert labor; we simply emailed instructions to the participants on how to install and use the app. Other studies that develop driving cycles involve the extensive use of expert labor whether using a chase car approach or in-vehicle logging. However, we are aware that the study design is not robust enough for the driving profiles we develop from our data to be distilled into a representative Pune driving cycle. We make no such claim but we do gather driving data from within the vehicle during peak hours that include several of the city's main arterials. As a result, the data we collected is sufficiently representative of peak hour commuting in Pune to provide us with insight into the real-world fuel economy performance of a typical Indian car. In the next stage of this project, we will design a robust study that takes into account the most heavily traveled routes by cars across all the major regions of the country and includes a large enough sample to develop an Indian Driving Cycle that is best representative of Indian driving behavior, traffic and car use. In this larger effort, the data collection method will be identical to this pilot project.

Data Cleansing And Driving Profile Development

We cleansed the data to exclude data points with very poor accuracy ratings. In addition, we analyzed the data to look for improbable changes in speed (going from 0 to 25 m/s in two seconds, for example) and smoothed those incidents to represent reasonable speed changes for a vehicle.

Once the data was received in the server and filtered, we analyzed all trips in each commute type to create three Pune driving profiles, comprised of the time variation of speed, acceleration, and grade:

a. **Pune 1** and **Pune 3** represent commutes 100% on city roads in a mix of heavy and light traffic conditions.

b. **Pune 2** represents a commute which is predominantly highway driving

The app collected time stamp, speed, bearing, and altitude. We derived the components of each driving profile from the Smart Phone data as follows:

- Time step (seconds) : $\Delta t = time\ stamp_{previous\ record} - time\ stamp_{current\ record}$
- Speed (meters/second): recorded by the device
- Acceleration (m/s/s)**:** $accel = \frac{speed_{previous\ record} - speed_{current\ record}}{\Delta t}$
- Change in altitude: $\Delta alt = altitude_{previous\ record} - altitude_{current\ record}$
- Grade (degrees): $grade = \arctan\left(\frac{\Delta alt}{speed * \Delta t}\right)$

Next, we simulated the performance of a typical Indian compact car on each of the three driving profiles we derived and on the MIDC.

Autonomie Simulation

Simulations were performed using the powertrain simulation tool, Autonomie (30). Autonomie combines physics and mathematics based submodels of individual powertrain components with models of the vehicle propulsion controller, and models of driver and environmental factors to create an overall powertrain model capable of predicting the performance of a vehicle under specified conditions. Drive cycles are specified as vehicle speed and grade profiles versus time. Major component submodels (such as the engine, batteries, transmission, etc.) use experimental measurements to specify performance and efficiency maps spanning the full range of possible operation for a component, however these maps can also be created using detailed modeling tools (for instance, using GTPower (31) for engine modeling).

A vehicle model was constructed for a conventional internal combustion engine vehicle resembling a Maruti Swift (most representative of the dominant models in the current and projected Indian fleet mix). The vehicle engine has a maximum power of 64 kW, a gross weight of 1415 kg and a 5-speed transmission, with gear ratios and a final drive ratio similar to those in a Maruti Swift. FIGURE 1 shows the interface of component submodels that make up the full vehicle powertrain model.

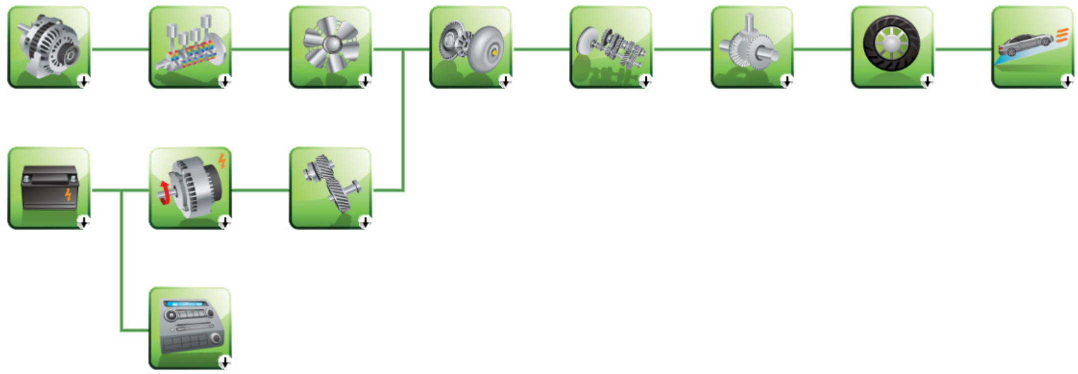

FIGURE 1 Collection of submodels of the vehicle powertrain model in Autonomie. From left to right and top to bottom: starter motor, engine, mechanical accessories, torque converter, transmission, differential, wheels, chassis, battery, alternator, torque coupling and electrical accessories.

RESULTS

Comparison of Pune Driving Profiles and the MIDC

FIGURE 2 compares the speed-time profiles of the three Pune driving profiles we developed from our data and the MIDC. The first 800 seconds of the MIDC is meant to represent city driving. When you compare this segment of the graph with the two city profiles from our data, Pune 1 and Pune 3, the differences between them and the MIDC are even stronger than we anticipated. TABLE 2 shows that the braking and acceleration events are substantially more frequent in Pune 1 and Pune 3 but each of these events are also much sharper than for the MIDC. Pune 1 is city driving in light, off-peak traffic and still shows almost as much stopping as the MIDC. In peak city traffic, represented by Pune 3, where the majority of car miles are logged, stopping is almost 8 times more frequent than the MIDC.

Finally, it is instructive to compare the highway driving representation in the MIDC and the Pune 2 profile, which is our highway profile. FIGURE 2 shows that Pune highway driving has almost no correlation with the MIDC's highway segment. There is no cruising in Pune 2 and the stop frequency is higher than in the highway portion of the MIDC. TABLE 2 shows that the magnitude of deceleration and acceleration in Pune 2 is just as high on average as in light city traffic (Pune 1) with the extreme events matching heavy city traffic (Pune 3). The highway portion of the MIDC, by contrast, shows relatively gentle acceleration and braking throughout. We expected these dramatic differences between the real-world driving profiles and the MIDC to translate into significant differences in vehicle performance, which is what we see in the Autonomie results.

TABLE 2 Characteristics of All 3 Pune Driving Profiles and the MIDC

	Units	Pune 1	Pune 2	Pune 3	MIDC
Max acceleration	m/s^2	3.68	3.39	5	1.06
Mean acceleration	m/s^2	0.23	0.26	0.43	0.16
Max deceleration	m/s^2	-2.15	-5.28	-6.19	-1.39
Cycle distance	miles	6	35.91	3.25	6.58
Driving Time	min	27.00	60.88	19.87	19.67
Maximum speed	mph	34.70	79.56	29.94	55.92
Mean speed	mph	12.12	36.24	11.65	26.70
Stop frequency	stops/mi	1.33	0.42	15.70	1.98

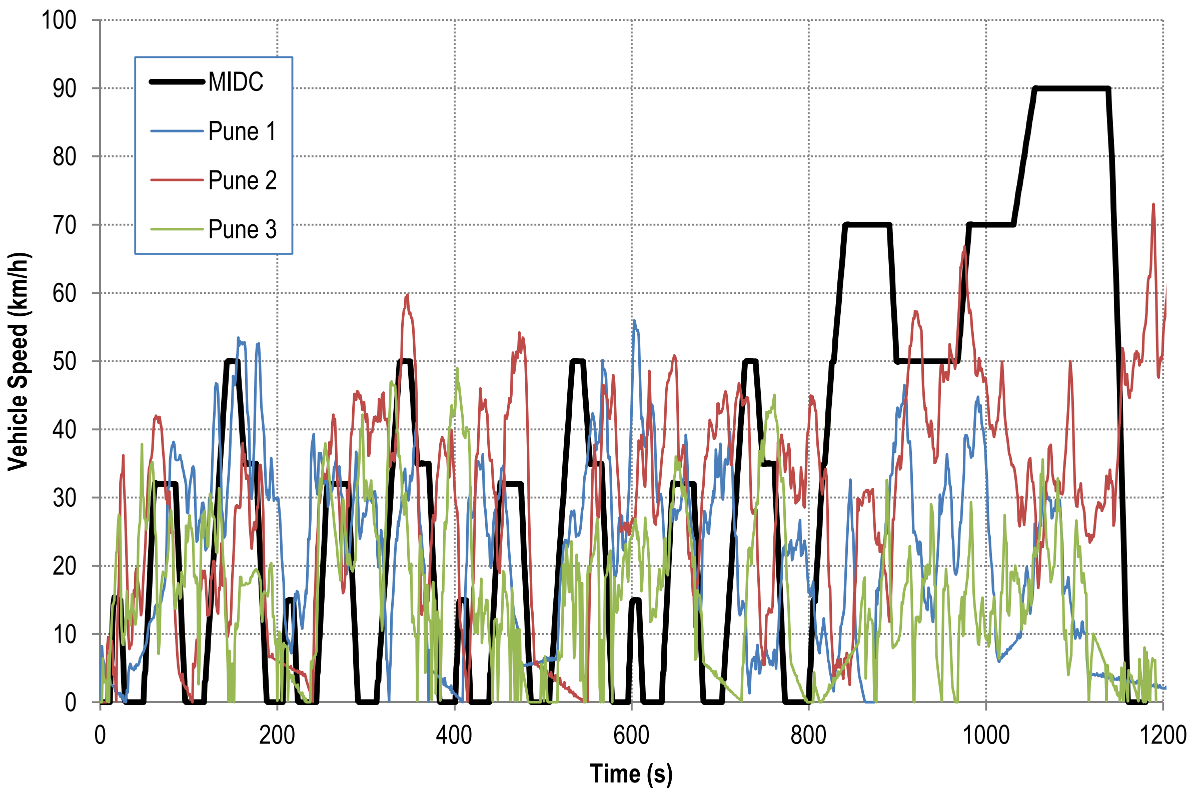

FIGURE 2 Speed-time plot of all 3 Pune driving profiles and the MIDC for the first 1200 seconds of each cycle. The Pune cycles show far more frequent speed variation and sharper acceleration events than the MIDC. This variation reflects driver experience in the busy streets of major Indian cities.

Autonomie Simulation Results

For each drive cycle, we modeled fuel use for the Swift-like compact car. Autonomie also allows calculations of GHG emissions per mile and power flow through individual vehicle components at any time instance during the simulation. Additionally, for detailed insight into the vehicle performance data that can be extracted from Autonomie, a 2-minute sample of the Pune 1 driving profile is shown in FIGURE 3, including vehicle speed, engine power output, engine speed, transmission gear state, and braking torque. By comparing the five plots within FIGURE 3, it is clear that engine operating characteristics, transmission shifting, and braking torque resemble what would actually occur in a vehicle. For instance, engine power and engine speed lie within reasonable levels, and peaks in these two quantities occur at time instances where rapid acceleration is requested. Engine speeds exhibit step increases or decreases based on transmission shifting events, and the time occurrence of the gear shifting is in line with requested vehicle speed. Finally, peaks in braking torque correspond with vehicle deceleration events, and the peaks in braking torque and engine power output never occur simultaneously. FIGURE 3 leads you to expect the Pune cycles to be fuel intensive: frequent and intense braking and re-acceleration ("start-stop driving") leads to more engine speed variance and engine power output per mile.

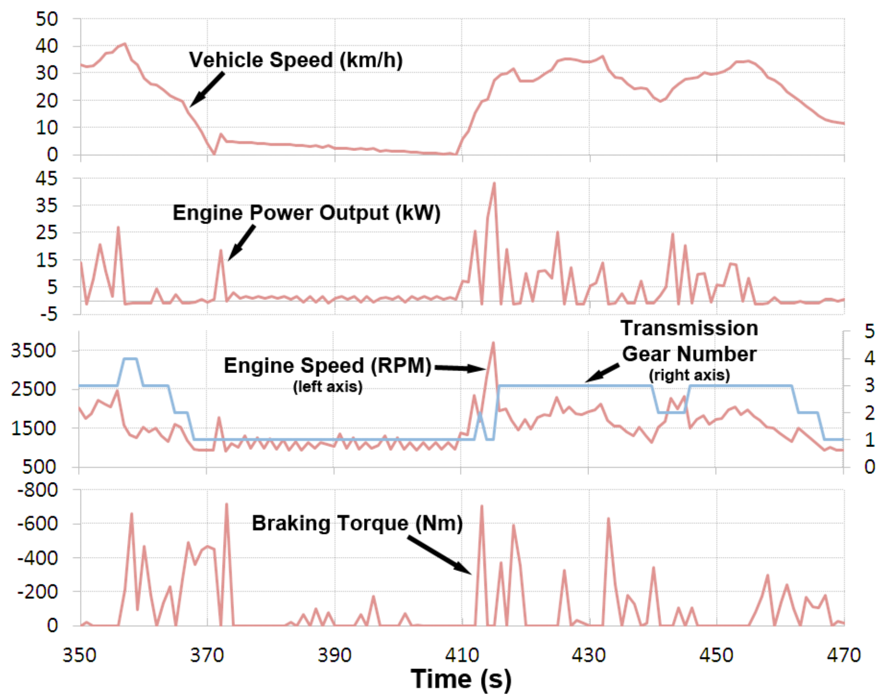

FIGURE 3 Two-minute snapshot of key vehicle parameters for the Pune 1 driving profile.

The vehicle performance results for each driving profile are shown in TABLE 3. The MIDC overestimates fuel economy by approximately 35% relative to the average of the three Pune profiles. When compared to the heavy city traffic driving profile (Pune 3), the MIDC underestimates fuel use by over 50%. Such substantial deviations make a strong case for much deeper investigation of the magnitude of the errors introduced by the current fuel economy test procedure. If our findings hold true, we can conclude it is imperative that India revise the driving cycle it currently uses for emissions and fuel economy testing.

TABLE 3 Compact Car Performance in Autonomie. The MIDC Overestimates Real World Fuel Economy by 35%

		Pune 1	**Pune 2**	**Pune 3**	**MIDC**
Distance Traveled	miles	5.23	35.76	3.21	6.57
Fuel Economy	mi/gal	29.27	28.86	22	41.91
Fuel Consumption	L/100 km	8.04	8.15	10.69	5.61
CO_2 emissions	g/mile	308.88	313.27	410.88	215.72
Engine efficiency	%	28.53	31.64	29.61	29.88

CONCLUSION AND POLICY IMPLICATIONS

This paper concludes that smart phones, using commercial apps, are capable of collecting data accurate and detailed enough to support significant advances in measuring, describing, and building models based on driving behavior and vehicle performance in India. We also demonstrate that we can get better data at a lower cost.

We found that a small sample of driving behavior in Pune, a city representative of many of the miles driven in India today and in the future, indicates that the use of the MIDC to rate car fuel economy could grossly overestimate the real-world fuel economy of the same car by 35% or more. At the individual level, inaccurate labels will mean that Indian car buyers cannot accurately plan a budget for the use and maintenance of a new car. At a societal level, the implications of these errors could be serious. Researchers usually assume that a vehicle's rated fuel economy is a good approximation of its real-world performance since the US and European ratings have been extensively refined to reflect this. Our findings imply that in the case of India a similar assumption could result in large-scale under-estimates in projections of oil demand, greenhouse gases and air pollution. This, in turn, could lead to inadequate policy, research and planning actions to solve the problems that bedevil Indian transport. Other implications of our findings are:

a. Better data collection about real driving behavior, if applied in regulation, can minimize discrepancies between rated and actual fuel economy and support policy development based on more realistic understanding of fuel use.

b. Such data collection can be done at a very small fraction of the traditional approach's cost, leveraging India's great cellular telephone leapfrog.

c. Furthermore, as India develops, driving behaviors may change. Ongoing measurement of behavior can enable an evolving national set of drive cycles for regulatory purposes.

d. Vehicle technologies that perform well at highly variable speeds (aka "start stop driving") will be especially beneficial in Indian cities, compared to Western cities (assuming the European cycle is a reasonable representation of driving in these locations). Such vehicles include conventional cars with larger starter motors, hybrid-electric, plug-in hybrid-electric, and pure-electric vehicles. Our group in undertaking research to quantify the benefits of these advanced drivetrains in India.

The ease with which we were able to collect this data also has implications for other GHG and petroleum concerns related to transportation behavior. For example research into understanding how new vehicle technologies will interact with Indian driving conditions can leverage similar smart phone-type data (32). Going further, this research can take advantage of the proliferation of off-the-shelf devices that plug into a vehicle's On-Board Diagnostic (OBDII) port, and send data from the vehicle's on-board computer to the smart phone via Bluetooth. The smart phone then marries engine data (such as air intake, pedal position, temperature, etc) to time stamps and locations, enhancing understanding of the vehicle's reaction to the driving conditions. Such devices are available at many commercial websites for less than $25.

India can use its phone fleet as speed probes to leapfrog in-road sensors for real-time traffic monitoring. Furthermore, Indians can use smart navigations apps on their phones that not only direct users to their destination in a timely, but also coordinate the advice given to calm traffic. India could also leapfrog the reliance on complex and often inaccurate transportation demand modeling based on origin/destination tables and extensive household travel surveys. By using directly measured data that does not fall victim to the failures of human memory like many surveys, and automatically tags trips by purpose, demographics, origin/destination, and more, Indian municipal policy makers and urban planners can accomplish more sophisticated planning at lower cost, leapfrogging Western transportation policy (33).

These examples are constrained to transportation that reduces GHGs. Dozens more examples exist in this vein, as well as potential applications for research, policy making, and policy implementation leveraging smart phones for automotive crash reduction, drunk driver detection, freight optimization, and more. And while India is especially able to take advantage of smart phones because of its mobile phone leapfrog, other developing nations will find many of the same benefits.

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