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Value of storage technologies for wind and solar energy

William A. Braff[1†], Joshua M. Mueller[2†] and Jessika E. Trancik[2,3*]

Wind and solar industries have grown rapidly in recent years but they still supply only a small fraction of global electricity. The continued growth of these industries to levels that significantly contribute to climate change mitigation will depend on whether they can compete against alternatives that provide high-value energy on demand. Energy storage can transform intermittent renewables for this purpose but cost improvement is needed. Evaluating diverse storage technologies on a common scale has proved a major challenge, however, owing to their widely varying performance along the two dimensions of energy and power costs. Here we devise a method to compare storage technologies, and set cost improvement targets. Some storage technologies today are shown to add value to solar and wind energy, but cost reduction is needed to reach widespread profitability. The optimal cost improvement trajectories, balancing energy and power costs to maximize value, are found to be relatively location invariant, and thus can inform broad industry and government technology development strategies.

Wind and solar energy technologies have attractive attributes including their zero direct carbon and other air-pollutant emissions (during operation)[1,2], their low water withdrawal and consumption requirements[3], the speed with which they can be installed[4], and the flexibility in the scale of their installations[5,6]. Innovation in these technologies has taken off in the past two decades[7]. Levelized electricity costs for both technologies have been dropping over the past few decades, with photovoltaics costs falling exceptionally quickly, by two orders of magnitude over the past 40 years[8,9]. The installed bases of solar and wind have grown markedly in recent decades, each at approximately 30% per year on average over the past 30 years, but together still supply only a few per cent of global electricity[9]. Although the global solar and wind energy resources are large, these technologies do not measurably contribute to climate change mitigation at current installations levels.

A variety of government policy-based incentives have supported the growth in solar and wind energy technologies in recent decades[10,11], but continued, rapid growth to levels that can help meet climate change mitigation goals will depend on whether the adoption of wind and solar can be made self-sustaining. Low-cost storage can play a pivotal role by converting intermittent wind and solar energy resources, which fluctuate over time with changes in weather, the diurnal cycle, and seasons[12], to electricity on demand that can be sold when most profitable, thereby increasing the value and attractiveness of these technologies to investors[13,14]. However, storage costs need to improve to achieve sizable adoption[15,16]. Quantifying the cost reduction needed has proved challenging and is the topic of this paper.

A range of stationary, large-scale energy storage technologies are in development[17]. These technologies have widely varying power and energy costs. Some storage technologies have more expensive power-related component costs (for example, pumped hydro power generation equipment) and cheaper energy-related costs (for example, pumped hydro natural reservoirs), and vice versa[18]. This paper aims to understand the value of storage for wind and solar energy at today's costs, and how technology costs need to improve, trading off energy and power costs, to reach profitability. This question can be answered only by examining the context in which storage technologies will be used, in particular the temporal variations in the energy price and intermittent energy resource. Here we investigate the potential for energy storage to increase the value of solar and wind energy in several US locations—in Massachusetts, Texas and California—with varying electricity price dynamics and solar and wind capacity factors.

As pointed out in earlier papers, comparing the costs of different storage technologies on a common scale is challenging because no single technology dominates the others along the two dimensions of energy and power costs (for example, refs 17,18). Studies have quantified the benefits of particular storage technologies for given locations and contexts of use, including for frequency regulation, energy arbitrage, converting intermittent renewables into baseload power, and increasing the profits of intermittent renewable energy (for example, refs 6,16,19–24), but past research has not shown how the benefit depends on the costs of different storage technologies. In this paper we address this gap and present a comparison of a spectrum of storage technologies (current and future hypothetical), showing quantitatively and across locations how the benefits of storage depend on storage technology costs. This approach allows for the quantification of technology cost performance targets for each given level of benefit. Specifically we focus on how the energy and power costs of storage affect the value added to wind and solar energy. This *ex ante* evaluation of storage options, on the basis of salient features of the technologies and contexts in which they will be used, can inform and accelerate their development through directed innovation[14,25].

The article is organized as follows. We first present the results of optimizing the discharge behaviour of a solar or wind plant combined with storage, for a fixed storage size, to maximize the revenue of the plant. We then optimize the storage size to maximize the value of the plant, where value is defined as the ratio of the plant revenue to the plant cost. The analysis is performed for a wide spectrum of storage energy and power costs. Finally, we assess the

[1]Department of Mechanical Engineering, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, Massachusetts 02139, USA.
[2]Institute for Data, Systems, and Society, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, Massachusetts 02139, USA.
[3]Santa Fe Institute, 1399 Hyde Park Road, Santa Fe, New Mexico 87501, USA. †These authors contributed equally to this work. *e-mail: trancik@mit.edu

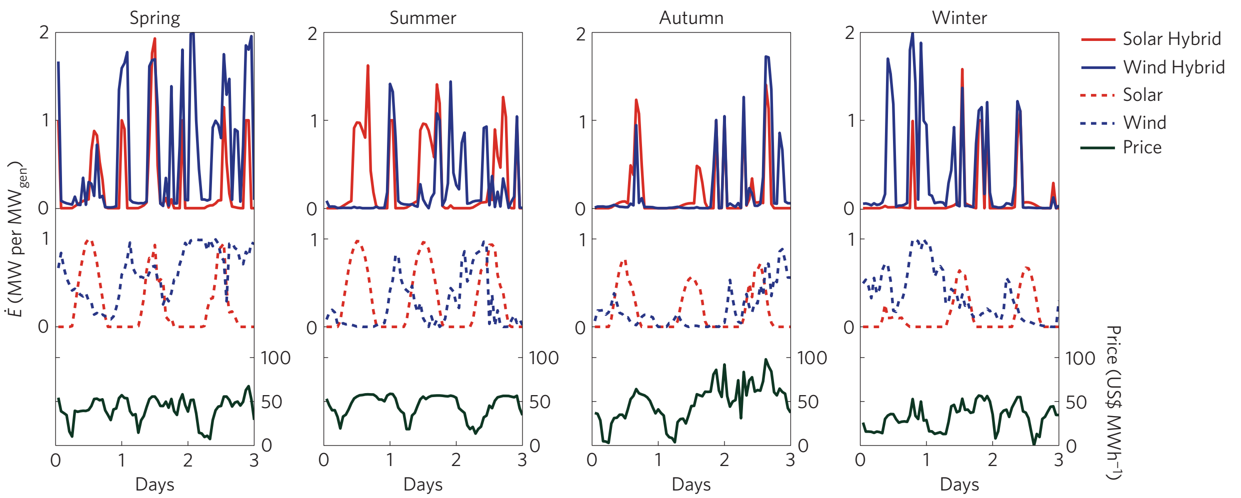

Figure 1 | Electricity output to maximize revenue from hypothetical hybrid renewable energy and storage plants. Results are shown for plants located in McCamey, Texas with a storage power $\dot{E}_{max}$ of 1 MW per MW$_{gen}$, and a duration h of 4 h (Supplementary Table 1). Data are shown here for a sample of three days in each season of the year, although the analysis considers all days of the year. Storage allows plant output to shift from the natural generation profile (middle row) to periods of high prices (bottom row: electricity price; top row: optimized output). Results for Palm Springs, California and Plymouth, Massachusetts are shown in Supplementary Figs 3 and 4, respectively.

value of current storage technologies, on the basis of their energy and power costs, and discuss optimal cost improvement trajectories across locations.

Optimizing electricity output to maximize revenue

Here we optimize the discharging behaviour of a hybrid plant, combining wind or solar generation with energy storage, to shift output from periods of low demand and low prices to periods of high demand and high prices (equation (2) in Methods). Both the energy resource and the electricity price, which vary over time and whose distribution over time is location dependent, determine the optimal charging and discharging behaviour of the system.

This effect is illustrated for the representative case of a storage system with a fixed size defined by a normalized power rating $\dot{E}_{max}$ of one MW per MW$_{gen}$ (storage power per unit rated power of solar or wind generation) and a duration h of 4 h, coupled with a solar or wind plant in Texas and operated over the course of three days in the spring, summer, autumn and winter (Fig. 1). Across both energy resources (wind and solar) and across locations (Texas, California and Massachusetts), incorporating storage results in a reduction of output during periods of low prices, and an increase in output during periods of high prices. The ability to output energy to the grid at peak power during periods of high price is limited, however, by the availability of sufficient renewable generation to charge the storage system in advance. Although the pricing in each of the three locations examined differs, the effect of storage in each case is to output electricity during periods of high pricing.

For a given plant, increasing the storage system size in terms of power and duration raises its average electricity selling price. The average selling price without storage is lower for wind than solar, but as the energy storage increases in size (per unit rated power of solar or wind generation), the pricing distribution and mean selling price become increasingly similar across the two energy resources (Supplementary Figs 6–8). However, the addition of storage power and duration comes at a cost, as explored in the next section.

Balancing revenue against cost to optimize storage size

Storage can increase the revenue generated by a solar or wind plant, but it also increases the capital costs of the plant. Here we optimize both the discharging behaviour, as done above, and the storage system size, to maximize the value of the electricity generation.

We quantify value using the dimensionless ratio χ, the ratio of the annual revenue to the annualized cost of the hybrid plant.

$$\chi = \frac{R_{total}}{\mathrm{CRF}(C_{gen} + \dot{E}_{max}(C^{power}_{storage} + hC^{energy}_{storage}))} \quad (1)$$

χ is determined by the revenue R_{total}, which is maximized through optimal discharging (equation (2)) at each storage size, and the costs of the hybrid plant. The plant cost is determined by the power capacity-related overnight construction cost of storage $C^{power}_{storage}$, the energy capacity-related overnight construction cost of storage $C^{energy}_{storage}$, the solar or wind generation cost C_{gen}, the capital recovery factor CRF (to annualize costs), and the storage size defined by peak power $\dot{E}_{max}$ and duration h (which are given per unit rated power of solar or wind generation). (See Supplementary Table 1 for a description of the parameter space considered.)

Figure 2 shows how χ varies as a function of the storage system power and duration, and the power- and energy-related costs, for the case of a hybrid wind plant sited in Texas with a generation cost of US\$1 W^{-1}. The contour plots in Fig. 2 illustrate that if a sufficiently inexpensive storage technology is used (for example, $C^{power}_{storage} \leq$ US\$130 kW^{-1} and $C^{energy}_{storage} \leq$ US\$130 kWh^{-1} for US\$1 W^{-1} Texas wind), the additional revenue generated by the storage system can outweigh its cost, thereby increasing the value, χ, of the system. The plots also show how the optimal system size (to achieve χ_{max}) depends on the energy and power-specific storage costs. As might be expected, storage systems with higher power-related costs performed better when specified with lower power, and storage systems with higher energy-related costs perform better when specified with lower energy (power $\dot{E}_{max}$ times duration h).

Figure 3 summarizes the change in χ with optimally sized storage across the three locations examined. Storage is more valuable for wind than solar in two out of the three locations studied (Texas and Massachusetts), but across all locations the benefit from storage is roughly similar across the two energy resources, in terms of the percentage increase in value due to the incorporation of optimally sized storage. However, the benefit of storage differs more significantly across locations, with a much higher percentage increase in value from storage occurring (across both energy resources) in Texas and California than in Massachusetts (Supplementary Table 5).

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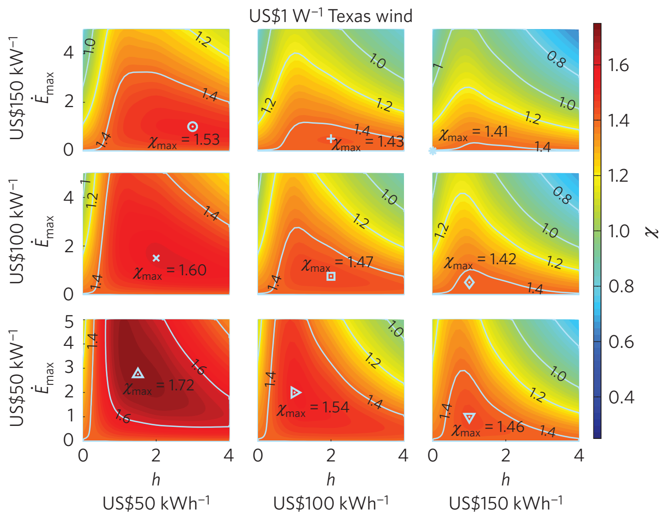

Figure 2 | χ values of a wind plant in Texas versus storage size. χ is shown for a range of storage sizes defined by power $\dot{E}_{max}$ (MW storage per MW generation) and duration h, for a wind C_{gen} of US\$1 W^{-1} and $C^{power}_{storage}$ and $C^{energy}_{storage}$ ranging from US\$50 kWh^{-1}–US\$150 kWh^{-1} and US\$50 kW^{-1}–US\$150 kW^{-1} respectively. The optimal storage system size is found for each storage energy- and power-related cost pair to maximize the value of the hybrid plant (χ_{max}). Similar plots for solar in Texas, and for wind and solar in Massachusetts and California, and for varying generation costs, are shown in Supplementary Figs 9–17.

Assessing the cost performance of storage technologies

The value of diverse storage technology options depends on their energy-related costs $C^{energy}_{storage}$ and power-related costs $C^{power}_{storage}$. Here we compare storage technologies that have been optimally sized to maximize χ for a given set of storage and generation costs, and energy resource and price dynamics in each location. The relationship between the dimensionless performance parameter χ and the energy and power costs of storage is shown in Fig. 4 across the three locations studied.

The results obtained can be compared with existing and future hypothetical energy storage technologies. Several papers have estimated the power- and energy-related costs of a number of energy storage technologies[17,18,26–30], finding that these costs can be treated as roughly modular because adding to power generation requires one set of components whereas adding to energy capacity requires another set of components (with caveats for batteries for which this distinction does not fully apply, see 'Discussion'). Widely ranging cost estimates have been reported in the literature[17,18,26–30] and are compared with our results in Fig. 5. We observe that some technologies available today[31], on the lower end of the range of reported cost estimates (Fig. 5), would add value to wind and solar energy. Included in this group of technologies are compressed air energy storage and pumped hydro storage for Texas wind or solar generation at US\$1.5 W^{-1} (or greater) (Fig. 5 and Supplementary Figs 41 and 42). This analysis allows for a quantitative comparison of disparate technologies. For example, despite power cost estimates that are several times larger for pumped hydro storage than lead–acid batteries, we find that pumped hydro storage technologies can significantly outperform lead–acid batteries for this application.

The results are further illuminated through specific examples. For the case of US\$3 W^{-1} solar generation and US\$450 kW^{-1} and US\$10 kWh^{-1} storage, roughly comparable to recently reported photovoltaics system costs[32,33] and the lower end of estimated costs of compressed air energy storage not utilizing natural gas (Fig. 5), the addition of optimally sized storage provides an approximately 25% increase in the plant value in Texas. (For lower photovoltaics

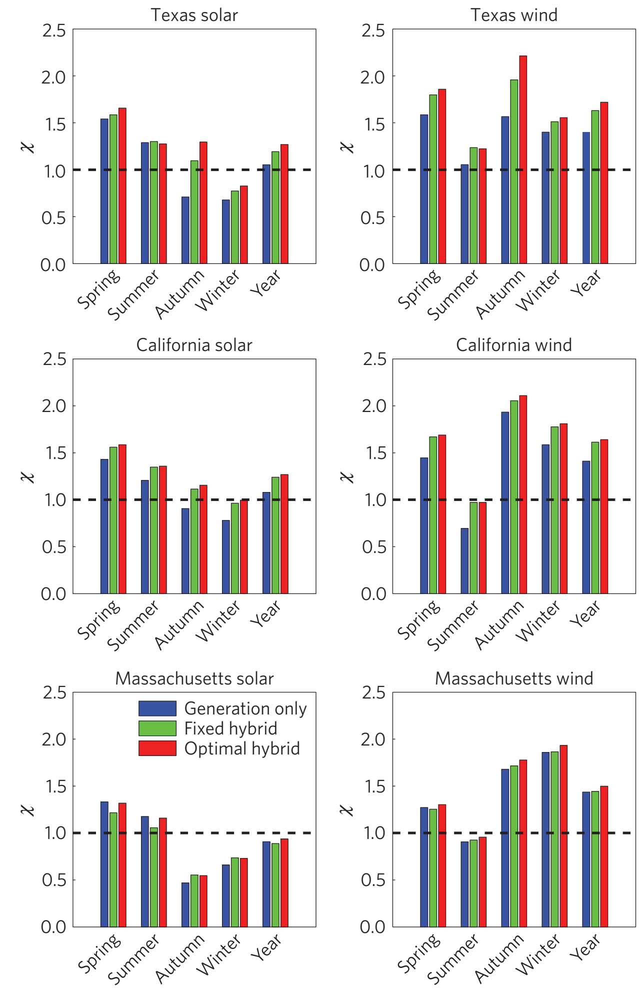

Figure 3 | Comparison of solar and wind plant χ values with and without storage. χ values are shown for plants without storage (generation only) and with storage for: a fixed storage size of $\dot{E}_{max} = 1$ MW per MW$_{gen}$ and $h = 4$ h of storage (fixed hybrid), and a storage system whose power and hours of storage ($\dot{E}_{max}$, h) have been optimized to match the energy resource and the location (optimal hybrid). Results are shown for a wind or solar generation cost of US\$1 W^{-1} and $C^{power}_{storage}$ and $C^{energy}_{storage}$ of US\$50 kW^{-1} and US\$50 kWh^{-1}, respectively. Results show the benefits of size-optimized storage across energy resources (solar and wind) and locations (Massachusetts, Texas and California), where storage systems are sized to maximize the ratio of annual revenue to cost, χ (and therefore can lead to sub-optimally sized storage in a particular season). The percentage increase in value due to optimally sized storage is given in Supplementary Table 5 for a range of storage and generation costs.

systems costs of US\$2 W^{-1}, comparable to several recent utility-scale cost estimates[33,34], compressed air energy storage also adds value.) However, at these generation and storage costs the system does not reach a χ value of 1, where revenue equals cost and the system becomes profitable (Supplementary Fig. 19). At these costs, it is advantageous to incorporate storage but subsidies are still required for the overall system to be profitable. For the case of US\$450 kW^{-1} and US\$10 kWh^{-1} storage and US\$1.5 W^{-1} wind generation (roughly comparable to recently reported costs[34,35]) storage adds approximately 11% additional value in Texas and χ just reaches 1, the profitability threshold (Supplementary Fig. 18). In comparison, for the case of US\$50 kW^{-1} and US\$50 kWh^{-1} and US\$1 W^{-1} solar or wind generation, which are aspirational costs, χ significantly exceeds 1, the profitability threshold, and storage adds roughly 20% to the value of the system χ as shown in Fig. 3.

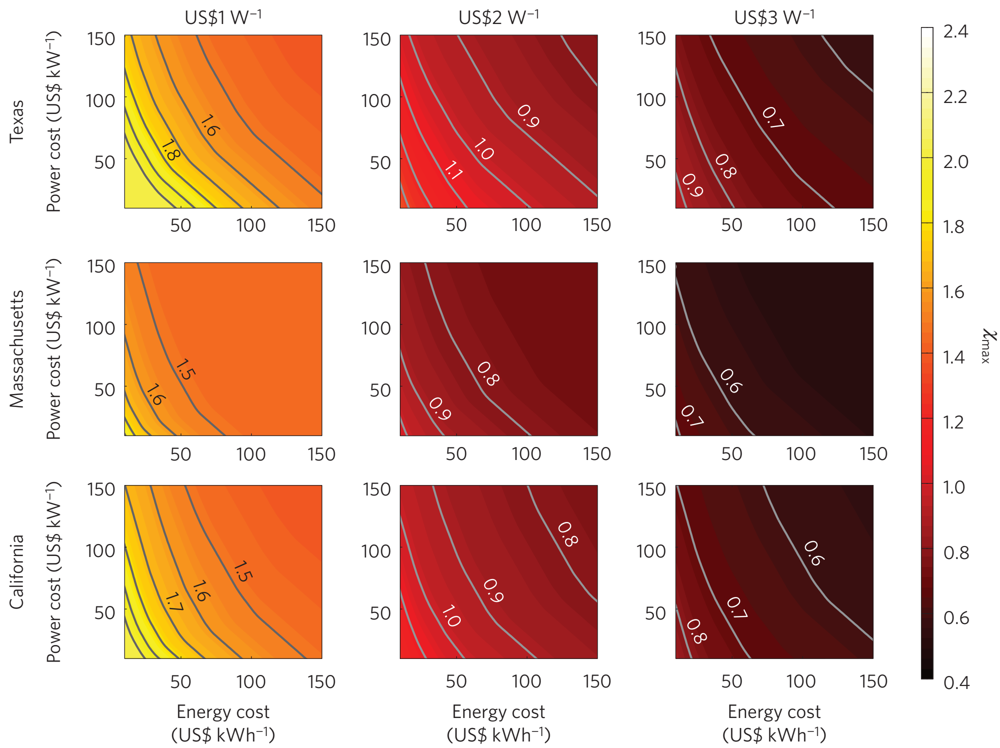

Figure 4 | Value of a hybrid wind and storage plant as a function of location, renewable generation costs, and storage costs. A range of generation costs (top row labels), and $C^{\text{power}}_{\text{storage}}$ and $C^{\text{energy}}_{\text{storage}}$ are shown. The size of storage ($\dot{E}_{\max}$, h) has been optimized at all points on the plot to maximize χ. (The top left panel shows the $\chi_{\max}$ data from Fig. 2.) For each contour of constant $\chi_{\max}$, the slopes were found to be roughly consistent across locations and to be determined by the duration of electricity price spikes (Supplementary Figs 43 and 44). A corresponding plot for solar is available in Supplementary Fig. 25.

As the cost of the solar and wind generation technology drops, the cost of storage must also drop to continue to add value (Fig. 5). This is because if generation costs are low enough relative to storage costs, it is more valuable to add generation capacity than storage capacity, even though this means that discharging cannot be optimized to increase revenue. As storage costs decrease relative to generation costs, the ability to increase revenue more than compensates for the additional cost of storage (equation (1)).

Although χ values change across locations, the slopes of the contour lines of constant χ (iso-χ lines) are relatively location independent, suggesting a power to energy cost trade-off that is roughly consistent across locations (Fig. 4). The power to energy cost trade-off of storage technologies is also similar across the two energy resources. This means that the direction of optimal improvement in energy and power costs is similar across the three locations and two energy resources for any given storage technology. This is important because it means that the results reported here can be used to inform industry and government technology development strategies, including investment in research and development of storage technologies for both intermittent energy resources and diverse locations. Further study is required to determine how widely this applies across locations (see 'Discussion').

The similarity across locations and energy resources in the slopes of the iso-χ lines can be attributed to commonalities in the electricity price dynamics across locations. The distribution of the duration of price spikes was found to be similar across the locations studied (Supplementary Fig. 44) and to define the slopes of the iso-χ lines (Supplementary Fig. 43).

Discussion

Our results suggest that storage technologies can substantially increase the value of wind and solar energy. For example, we find that storage at costs comparable to several published estimates for compressed air energy storage and pumped hydro storage can add value to wind and solar energy in Texas and California at current costs. However, to reach profitability without subsidies across the locations studied, further cost improvement is needed in wind and solar generation costs and storage costs. Furthermore, as renewable generation costs decrease over time, storage costs must also decrease to add value.

Importantly, the results presented here point to cost performance targets for storage technologies to add value and for the renewable energy and storage hybrid plant to reach profitability. For example, researchers and research and development managers in the public and private sectors might use the results to assess the potential benefit of pursuing one technology design over another, or one class of storage technology over another, according to its distance from a cost threshold and potential for cost improvement along energy and power cost dimensions. Despite differences across the locations studied in the benefits of adding storage, the direction of optimal storage cost improvement, balancing decreases in the energy- and power-related costs of storage, is similar across locations. Thus, the results can inform a roadmap for cost improvement to guide broad government and industry technology development strategies.

Additional research is needed to assess the costs of storage technologies today, as current estimates span a large range (Fig. 5). The assumption of modular power and energy costs[17,18,26–30] may be more appropriate for some technologies (for example, compressed air energy storage) and less for others (for example, batteries) and deserves further investigation. For batteries, many studies nonetheless used the approximation of modular costs[17,18,27,28] and assign shared component costs to the energy cost estimate. As energy is often the limiting factor for a given total investment in a stationary battery[36], this treatment is a reasonable approximation. Additionally, the cycling behaviour of storage will affect the

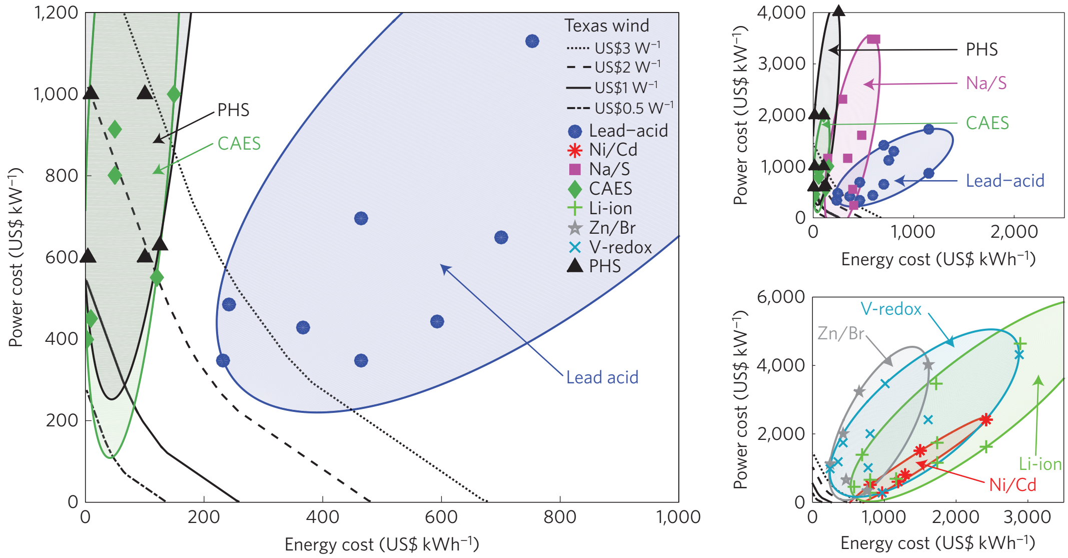

Figure 5 | Energy storage technology costs compared with value-adding cost thresholds. Cost intensities of a range of energy storage technologies[17,18,26–30] overlaid on lines, each for a given wind generation cost, which show the threshold storage cost intensities at which it becomes valuable to incorporate storage into a Texas wind plant. CAES: compressed air energy storage; PHS: pumped hydro storage; lead–acid, Ni/Cd, Na/S, Li-ion: batteries; Zn/Br, V-redox: flow batteries. Results for solar and other locations are shown in Supplementary Figs 28–32. The sensitivity of storage cost estimates to additional operations and maintenance costs, and extended construction times, as well as fuel costs (for CAES utilizing natural gas), are shown in Supplementary Figs 35–42. Ellipses are plotted to encapsulate the range of cost estimates for each storage technology, while minimizing the shaded area. The ellipses are visual guides and do not represent joint probability distributions; all results discussed in the paper refer to the data points themselves, and not the shaded regions.

lifetime capacities of technologies differently[37,38]. This effect is not represented in our model but will have a significantly smaller effect on storage capacity costs than the span of costs reported in the literature. These refinements can be incorporated in the future as cost estimates for storage technologies are further resolved.

We have focused here on increasing revenue from the sale of renewable energy but note that storage technologies installed for this purpose might generate additional revenue streams from other services that we do not consider, including frequency regulation, meeting installed power capacity requirements, and arbitrage that is not constrained by the renewable energy resource. This additional revenue could increase the added value of storage relative to the results presented in this paper. Assessing the scale of this added value, and the degree to which it is predictable and can be used to distinguish between candidate storage technologies, is a subject for future investigation.

Furthermore, the analysis performed here is for a low-penetration case in which the solar and wind plants are price takers, and do not measurably influence the electricity price over time. If renewables grow sufficiently to significantly influence the price time series of electricity in the locations studied, the results would change. The changing cost of electricity from other sources with which renewables are competing, or changing demand patterns and market structure, could also affect the results presented. Further study of the changes in electricity price dynamics over time and space is a subject for future research.

Deploying hybrid systems today could support the near-term growth in solar and wind, in contexts where storage technologies add value, as well as the investment and improvement in storage technologies that are needed to eventually allow greater intermittent renewables market share without long-distance electricity transmission or carbon-emitting back-up generation. Understanding and maximizing the value of storage in today's small market share context is therefore critical to eventually achieving the large-scale adoption of very-low carbon-intensity intermittent renewables.

Methods

Methods and any associated references are available in the online version of the paper.

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Author contributions

J.E.T designed the study; W.A.B., J.M.M. and J.E.T. built the model and performed the analysis; J.E.T., W.A.B. and J.M.M. wrote the paper.

Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to J.E.T.

Competing financial interests

The authors declare no competing financial interests.

Methods

The analysis involved three steps. First, hourly electricity pricing data and wind and solar energy resource availability data were compiled for each of the three US locations studied. Results are presented for the year 2004, a conservative year in which the value of storage is lower than it is in the other years studied. The analysis of other years for which data are available is given in the Supplementary Information. All dollar values in the paper and Supplementary Information are presented in 2004 currency. Second, the charging and discharging behaviour of a set of hypothetical hybrid renewable energy and storage plants with a range of fixed storage sizes was optimized to maximize revenue. Third, an optimal storage system size for each location and energy resource was determined to maximize the value (annual revenue divided by annualized cost) of the wind and solar energy with storage plant, for a range of energy- and power-related costs of storage.

Site selection. Three geographic sites were examined as locations for hypothetical wind and solar plants with storage: McCamey, Texas, Palm Springs, California, and Plymouth, Massachusetts. The Texas site was chosen as an example of a high-performing wind site, with an average capacity factor of 32% over the period examined (where capacity factor is defined as the annual output of a hypothetical plant divided by the output if operated continuously at the rated power capacity). The California site was selected as a high-performing solar site, with an average capacity factor of 23%. The Massachusetts site was chosen as a case where neither wind nor solar was particularly high performing, with capacity factors of 26% and 16%, respectively. Supplementary Fig. 2 illustrates the distribution of generation and pricing for these three sites. Data for zonal real-time (hourly) pricing were obtained from ISO New England (http://www.iso-ne.com), ERCOT (http://www.ercot.com) and CAISO (http://www.caiso.com). To simulate the performance of a hypothetical wind turbine or solar array, local windspeed and solar insolation data were obtained from the Eastern and Western National Wind Integration Datasets and the National Solar Radiation Database[39], and then transformed to time-dependent output per megawatt installed using published performance data for a Vestas V90 3 MW wind turbine that aligns to face the wind (http://www.vestas.com) and a static photovoltaic system that reaches its maximum output when exposed to an insolation of 1 kW m^{-2} (corresponding to standard test conditions).

Optimization of charging and discharging to maximize revenue. Per-hour charging and discharging of the storage system, and the direct sale of solar- and wind-generated electricity were optimized to achieve maximum revenue for a hypothetical hybrid storage and generation plant at each site, given the electricity price and energy resource availability over time and subject to system power and energy constraints. The optimization was performed in three-week intervals over the course of a year, with a one-week overlap between each interval to prevent discontinuities. The charge rate was capped at the real-time output of the generation resource, and the energy available for discharge was adjusted by a round-trip efficiency of 90%. To reduce the computational expense of the optimization, the simulation considered charging and discharging separately so that a linear solution technique could be employed. The ability of the simulation to find the global optimum was confirmed by comparison with an analytical solution in the case of arbitrage that is not constrained by the renewable energy resource.

The optimization routine for each three-week segment ($N = 504$ h) can be expressed in terms of the real-time price $P(t)$, the generation profile $x_{\mathrm{generation}}(t)$, storage round-trip efficiency η, peak power $\dot{E}_{\max}$, and duration h as:

$$R_{\mathrm{total}} = \max\left(\sum_{t=0}^{N} P(t)\left(x_{\mathrm{generation}}(t) + x_{\mathrm{discharge}}(t) - x_{\mathrm{charge}}(t)/\eta\right)\right)$$

subject to:

$$0 \le x_{\mathrm{discharge}} \le \dot{E}_{\max}$$

$$0 \le x_{\mathrm{charge}} \le \min(\eta x_{\mathrm{generation}}(t), \eta \dot{E}_{\max})$$

$$0 \le \sum_{t=0}^{N}\left(x_{\mathrm{charge}}(t) - x_{\mathrm{discharge}}(t)\right) \le h\dot{E}_{\max} \qquad (2)$$

An offset is included in the energy constraint for each optimization period to account for the amount of energy stored in the system at the beginning of the optimization period. The optimization protocol serves to temporally shift the output of the system to periods of high market pricing (often coinciding with times of peak demand), subject to the constraint that any energy to pass through the storage system pays an efficiency penalty.

We studied the case where hybrid renewables and storage systems are price takers in the spot market, which is an adequate approximation for small penetration levels. It is also assumed that the system operator has perfect information about future three-week prices and resource availability. This approach employs the assumption supported by earlier work that the overestimate in revenue as a result of complete future knowledge is small[40–43].

Value of optimally sized storage. A dimensionless performance metric χ was used to quantify the value of the energy generated, which is the ratio of the optimized annual revenue generated (equation (2)) and the annualized plant cost (equation (1)). Plant overnight construction costs are given as the sum of the storage and generation costs per unit rated power of installed solar or wind generation ($C_{\mathrm{gen}} + \dot{E}_{\max}(C^{\mathrm{power}}_{\mathrm{storage}} + hC^{\mathrm{energy}}_{\mathrm{storage}})$). To determine the annualized plant capital costs, the overnight construction costs are multiplied by a capital recovery factor, CRF(i, n), defined as CRF$(i,n) = i(1+i)^n/((1+i)^n - 1)$, with $n = 20$ years and $i = 5\%$ (ref. 15). The capital recovery factor is the fraction of a loan that must be paid back annually, assuming a stream of equal payments over n years and an annual interest rate i. The plant costs are approximated in this framework by plant capital costs (for example, for hypothetical storage technologies at various cost points in Fig. 4). This approximation is reasonable given the dominance of the capital cost portion of total plant costs for most storage technologies, although we discuss below the effect of including estimated operations and maintenance costs for several storage technologies available at present. Plant performance χ was calculated using equation (1) over a wide range of system configurations, technology costs and locations, as summarized in Supplementary Table 1.

The storage size, defined by the storage power and storage duration, was chosen to maximize χ given the storage cost, where storage cost is defined by the power-related cost per kilowatt and energy-related cost per kilowatt-hour. Storage sizes were simulated in increments of 1/4 h and 1/2 W_{storage} per $W_{\mathrm{generation}}$.

To compare the model results to the cost of candidate storage technologies today, the costs of energy and power of various storage technologies were taken from the literature, drawing inclusively on recent efforts to identify the modular power- and energy-related cost components of a storage system[17,18,26–30]. These wide-ranging costs are reported in the literature as rough estimates, mixing cost data and engineering estimates (as is common for technologies that have limited or no market adoption). These cost estimates are treated as 2004 real dollars (owing to a lack of information otherwise) for the comparison to revenue in 2004 (an assumption that has a minor effect on the storage technology evaluation as compared to the wide range of reported storage costs for each technology). Technologies are modelled with a round-trip efficiency of 90% as technology-specific refinements to this estimate (which are themselves uncertain) have little effect compared to the wide range of storage costs reported. Replacement costs for storage technologies with estimated lifetimes of less than 20 years (according to the following references:[17,18,26–30]) are included in the storage overnight construction costs, assuming a constant power-related cost per kilowatt and energy-related cost per kilowatt-hour (in nominal dollars) in future years and discounting (with a 5% nominal discount rate, although the conclusions are robust to a reasonable range of assumed rates) the cost of future replacement to determine its present value at the start of plant operation.

In the Supplementary Information (Supplementary Figs 35–42) we explore the sensitivity of the storage technology costs shown in Fig. 5 to estimated operations and maintenance costs, extended construction lead times, and fuel costs for compressed air energy storage. Despite uncertainty in estimates of these additional costs[30], the sensitivity analysis provides some insight. The general technology comparisons (that is, the relative positions of ellipses shown in Fig. 5) are found to be robust to the inclusion of these additional costs. Furthermore, the uncertainty in storage technology cost estimates arises mainly from uncertainty in the capital costs.

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Potential for widespread electrification of personal vehicle travel in the United States

Zachary A. Needell[1,2], James McNerney[1], Michael T. Chang[1] and Jessika E. Trancik[1,3*]

Electric vehicles can contribute to climate change mitigation if coupled with decarbonized electricity, but only if vehicle range matches travellers' needs. Evaluating electric vehicle range against a population's needs is challenging because detailed driving behaviour must be taken into account. Here we develop a model to combine information from coarse-grained but expansive travel surveys with high-resolution GPS data to estimate the energy requirements of personal vehicle trips across the US. We find that the energy requirements of 87% of vehicle-days could be met by an existing, affordable electric vehicle. This percentage is markedly similar across diverse cities, even when per capita gasoline consumption differs significantly. We also find that for the highest-energy days, other vehicle technologies are likely to be needed even as batteries improve and charging infrastructure expands. Car sharing or other means to serve this small number of high-energy days could play an important role in the electrification and decarbonization of transportation.

Transportation accounts for 28% of US energy use and 34% of US greenhouse gas emissions, the majority coming from light-duty vehicles making personal trips—people commuting to work, driving to social events, and performing errands in cars and light trucks[1,2]. The United States has committed to reducing carbon emissions by 26% to 28% from 2005 levels by 2025[3], even while total vehicle miles travelled are expected to stay constant or increase[1,4,5]. Battery electric vehicles (BEVs) could contribute to reducing transportation-related greenhouse gas emissions, offering some emissions savings even with today's fossil-fuel-dominated electricity supply mix[6–8]. If coupled with a decarbonized electricity supply mix, BEVs could dramatically cut transportation emissions[9–11]. Indeed, the extent and pace of the transition to BEVs may determine whether the US meets its emissions reduction goals[12].

There are several potential barriers to achieving the widespread electrification of transportation, however, including infrastructure integration challenges and various factors limiting consumer purchases of electric vehicles[13,14]. Transportation electrification would expand the demand for electricity and could significantly change the temporal and spatial patterns of demand[15], potentially producing stress on existing infrastructure[16]. Supporting these changes may require an expansion of electricity supply infrastructure and innovation in how the electrical grid is managed. Relying primarily on night-time charging would alleviate some of these integration concerns because vehicles could plug in at home when some power plants sit idle[6], and would avoid the need for ubiquitous charging infrastructure or battery swap stations[17]. Where available, workplace charging using on-site solar generation could offer an alternative, non-invasive charging option during the week, which may be particularly helpful if vehicles cannot charge at home[18,19]. Once-daily charging would, however, require BEVs that cover the energy needs of an entire day's travel.

The limited range of BEVs is perhaps the most significant barrier to the large-scale adoption of BEVs[11], even with daytime charging available. Both real and imagined range constraints—defined by the vehicle range, available charging infrastructure, and the range requirements of drivers—can lead to 'range anxiety' that limits the adoption of BEVs[20]. Quantifying range constraints, which is the subject of this paper, may help alleviate this anxiety[21]. Addressing range anxiety is a necessary though not sufficient condition for the widespread growth in adoption of BEVs. Satisfying consumer preferences for vehicle performance and aesthetics will also be important, as will financing options to offset the purchase price of BEVs[22].

Several previous studies examine the range requirements of personal vehicle travel. For example, a study following 255 Seattle households found that a vehicle with 100-mile range would meet the needs of most single-car households while requiring behavioural modification on no more than 5% of days[23]. These studies and other research on aggregate travel behaviour in the US[24,25] provide insight into vehicle range requirements. However, a question remains: how do these requirements compare with the range achievable by BEVs? BEV range has been shown to depend sensitively on the second-by-second velocity profile followed by the vehicle[26], and other factors such as ambient temperature and associated climate control auxiliary energy consumption[27].

Past studies of travel demand uncovered significant geographic variation in the energy requirements of transportation[28], with per capita energy consumption differing up to 50% across US cities, in inverse correlation with factors such as population density and per capita spending on public transit[29,30]. These conclusions might suggest, at first glance, that BEV adoption potential would also vary considerably across cities and that high-energy-consuming cities would have lower BEV adoption potential because of a dependence on long-distance trips in personal vehicles.

Here, we evaluate BEV range and adoption potential against driving patterns across the United States, drawing on information in various data sets to cover millions of trips across the US and to incorporate the effects of second-by-second velocity profiles and hourly ambient temperature. This paper thus presents a comprehensive yet high-fidelity analysis of vehicle range constraints to BEV adoption. We find that a large percentage of daily personal vehicle energy requirements across the US as a whole, and within major cities, can be met by a relatively inexpensive BEV on the market

[1]Institute for Data, Systems, and Society, Massachusetts Institute of Technology, Cambridge, Massachusetts 02139, USA. [2]Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, Cambridge, Massachusetts 02139, USA. [3]Santa Fe Institute, Santa Fe, New Mexico 87501, USA. *e-mail: trancik@mit.edu

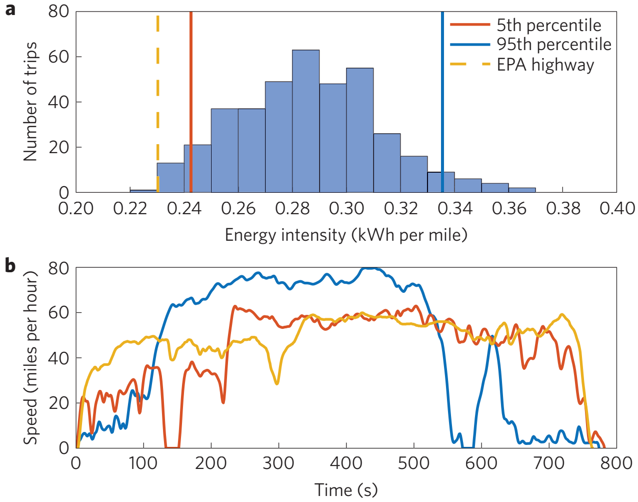

Figure 1 | Energy intensities and velocity histories of trips with similar distances and durations. Trips shown are similar to the EPA highway (HWFET) drive cycle in terms of distance and duration but have differing energy intensities, demonstrating the importance of considering velocity histories in determining trip energy requirements. **a**, Fuel economy distribution (kWh per mile) for the 2013 Nissan Leaf, for trips in the GPS database that have a distance and duration similar to the EPA HWFET. **b**, Velocity profiles of the three trips marked on the above plot.

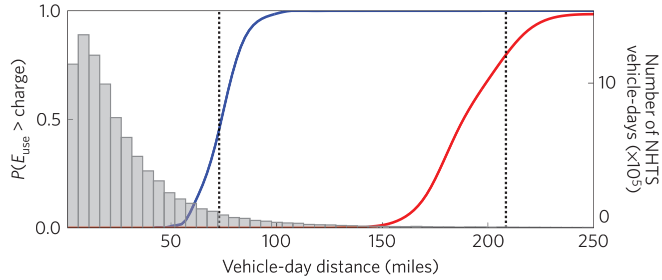

Figure 2 | Probabilistic model of BEV range given observed nationwide travel behaviour. The probability that a vehicle travelling a given daily distance exceeds a battery energy threshold is shown for a current and future improved battery technology. Blue line: current usable battery capacity of 19.2 kWh in a vehicle modelled after the 2013 Nissan Leaf. Red line: identical vehicle with the same battery mass but 55.0 kWh usable battery capacity, based on an ARPA-E battery specific energy target. Dotted lines: ranges for the current battery capacity (19.2 kWh) and the ARPA-E target capacity (55.0 kWh) based on the EPA-estimated average vehicle fuel economy. Grey bars: histogram of nationwide vehicle-day driving distance.

today. Our cross-city comparison shows that the constraint imposed on BEV adoption potential by vehicle range is, in fact, remarkably similar across different cities. The Nissan Leaf, our representative vehicle, falls below the average and median lifetime cost of the 94 most popular vehicles on the US market today[31]. We estimate that this vehicle can meet the energy requirements of 87% of vehicle-days across the US, and 84–93% in 12 of the most populous metropolitan areas, even if relying only on night-time charging. This 87% of vehicle-days accounts for 61% of personal vehicle gasoline consumption in the US. Improvements to the energy density, specific energy, and cost per unit energy capacity of batteries would increase these daily vehicle and gasoline substitution percentages. However, a small number of very-high-energy days, as evidenced by a heavy-tailed distribution of daily vehicle energy requirements, translates to diminishing returns to battery improvement.

Probabilistic model of BEV range

The model presented here provides a probabilistic view of BEV range. This model, 'TripEnergy', draws on: information from the National Household Travel Survey (NHTS)[2] database on the distance and duration of trips taken by a representative sample of drivers across the US; data on regional temperature at an hourly timescale[32] (Supplementary Fig. 2); GPS data sets giving second-by-second velocity profile information across a diverse set of trips (for example, ref. 33, Supplementary Note 1, Supplementary Fig. 1 and Supplementary Table 1); and the results of vehicle fuel economy tests[34] (Supplementary Table 2). Using a conditional bootstrap procedure, we match NHTS trips to a set of possible drive cycles (Fig. 1 and Supplementary Fig. 3) and use information on the time and location of trips to estimate climate control auxiliary energy use (Methods and Supplementary Note 2). The model has been calibrated and validated through extensive testing (Supplementary Note 3 and Supplementary Figs 10–12).

The results demonstrate the importance of considering driving behaviour in estimating BEV range (Fig. 2). While the US Environmental Protection Agency (EPA) publishes estimated ranges for particular vehicles (Supplementary Table 3), the realized range—the distance that can be driven on one charge—is influenced by several factors and can vary from trip to trip. These factors include the use of auxiliary power for heating or cooling and the velocity profile of the trips taken. These factors can have a large impact on vehicle range (Figs 1 and 2 and Supplementary Fig. 6). Given EPA-estimated average fuel economy of 116 MPGe, battery capacity of 24 kWh, allowed depth of discharge of 80% (in keeping with the Leaf's 'long life mode'[35], Supplementary Note 1), and charging losses of 10%, we would predict the 2013 Nissan Leaf to have a range of 73 miles. Our model predicts 74 miles as the median range—the distance for which half of all vehicle-days could be covered on one charge. However, variation in trip velocity profiles and auxiliary power use produces a distribution of ranges (Fig. 2), and our model predicts that 1 out of 20 of 58-mile vehicle-days could not be covered by existing batteries, and 1 out of 20 of 90-mile vehicle-days could.

Furthermore, application of the model reveals that the BEV's median range changes nonlinearly with battery capacity, because velocity profiles tend to differ between short- and long-distance travel days. As an example, increasing the battery's specific energy to an Advanced Research Projects Agency-Energy (ARPA-E) target value[36] of 200 kWh kg^{-1} while keeping its mass constant would increase usable battery capacity by 186% to 55 kWh. Doing so would increase the Leaf's median range to 173 miles, an increase of only 131%. The sub-linear relationship between range and battery capacity is due to the longer vehicle-days containing more long-distance highway driving—trips for which BEVs have a lower fuel economy than for inner-city trips[26,37,38] (Supplementary Fig. 9). This finding—the quantification of this sub-linear relationship—illustrates the value of a model that captures changing vehicle efficiency with the velocity profile and a comprehensive characterization of real-world travel behaviour.

Daily energy requirements and BEV adoption potential

We apply the model to personal vehicle travel across the US. Two metrics are presented here. The first is the daily vehicle adoption potential (DAP), which is defined as the percentage of vehicles per day that could be covered on one charge. The second metric is the gasoline substitution potential (GSP), which is the percentage of gasoline consumption that could be replaced by BEVs that charge once a day (see Supplementary Note 4). These metrics quantify a technical potential that is limited by range constraints for utilizing a BEV on a representative day, with only once-daily charging available. Individual days may diverge from these results, particularly those when many people are travelling long distances

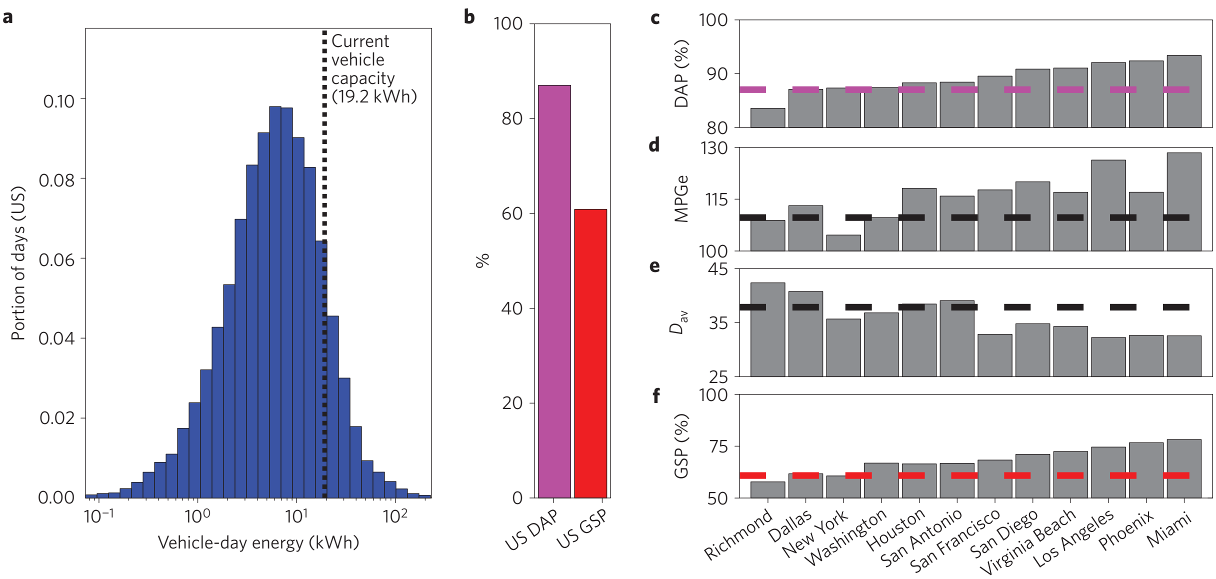

Figure 3 | Nationwide and city-specific BEV energy requirements evaluated against battery capacity. Energy capacity and requirements are calculated for the 2013 Nissan Leaf. **a**, Histogram of BEV vehicle-day energy consumption for the entire US (blue bars) compared with the usable battery capacity (dashed line). **b**, Daily vehicle adoption potential (DAP, purple) and gasoline substitution potential (GSP, red) across the US. **c**, City-wide values for daily vehicle adoption potential (DAP). **d**, Average fuel economy (in miles per gallon equivalent, MPGe). **e**, Average vehicle-day driving distance (in miles). **f**, Gasoline substitution potential (GSP). Horizontal dashed lines represent US averages.

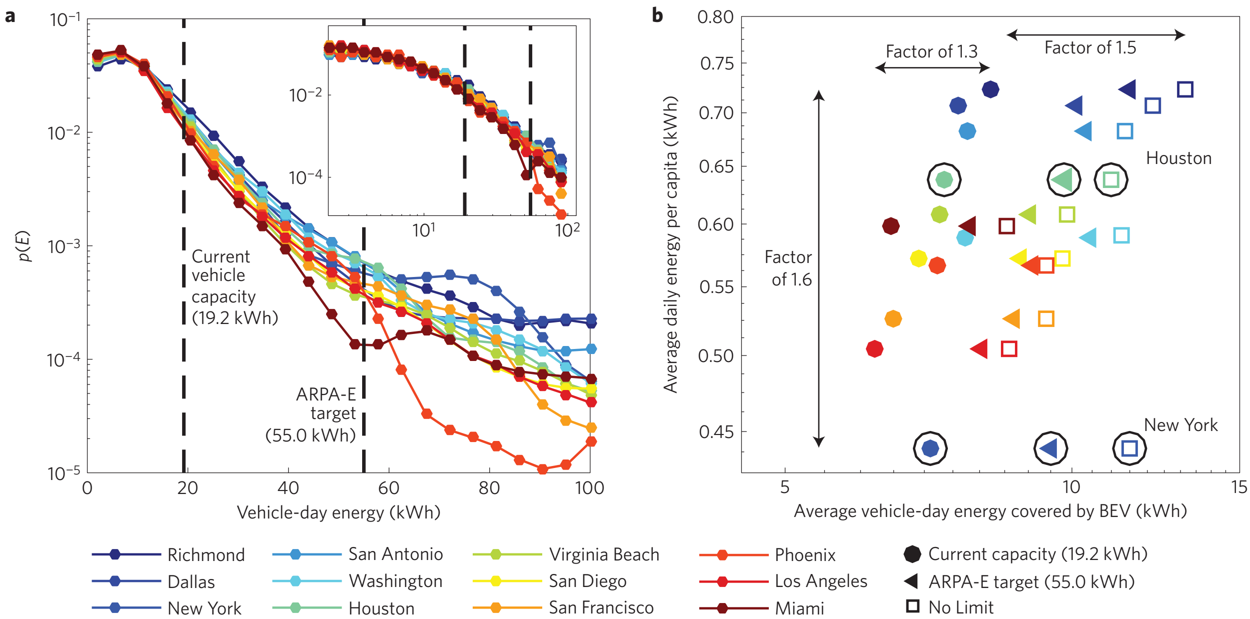

Figure 4 | Vehicle-day energy distributions in various cities and the differentiating effect of their heavy tails. a, Estimated vehicle-day probability distribution on a log–linear (inset: log–log) scale. The vertical lines represent usable battery capacity for the 2013 Leaf with current battery technology (19.2 kWh) and the ARPA-E target battery specific energy but the same battery mass (55 kWh). **b**, Average daily energy consumption (in personal vehicles) per capita and average daily energy consumption per vehicle driven. The *y* axis shows city-wide average energy consumption per capita, for the range of cities studied, assuming a BEV is used for all trips. The *x* axis shows mean BEV energy consumption per vehicle-day given different battery constraints: filled circles are based on a vehicle with current battery capacity (19.2 kWh); triangles on the ARPA-E target battery specific energy and the same battery mass (55 kWh); and squares on no capacity limit. The mean BEV energy consumption in each city shifts to the right as the battery capacity increases and more high-energy vehicle-days are included in the sample. The variability across cities also increases, from a factor of 1.3 for the current Leaf to 1.5 for a BEV with no range constraints. For illustration, New York and Houston are highlighted with open circles. Colours in both panels denote different cities, as indicated by the key.

(for example, Thanksgiving[39]). For BEV ownership to rise to these levels, convenient options should be available to meet travellers' needs on all days.

Figure 3 shows the energy distribution for personal vehicle-days in the US, as well as the DAP and GSP for the US in aggregate. Results are also shown for the 12 metropolitan areas with the largest number of NHTS-respondent households. We find a DAP of 87.0% for the US in aggregate. The corresponding GSP is 60.9%, lower than the DAP because the 13.0% of trips not covered by the BEV account for a disproportionate amount of energy consumption.

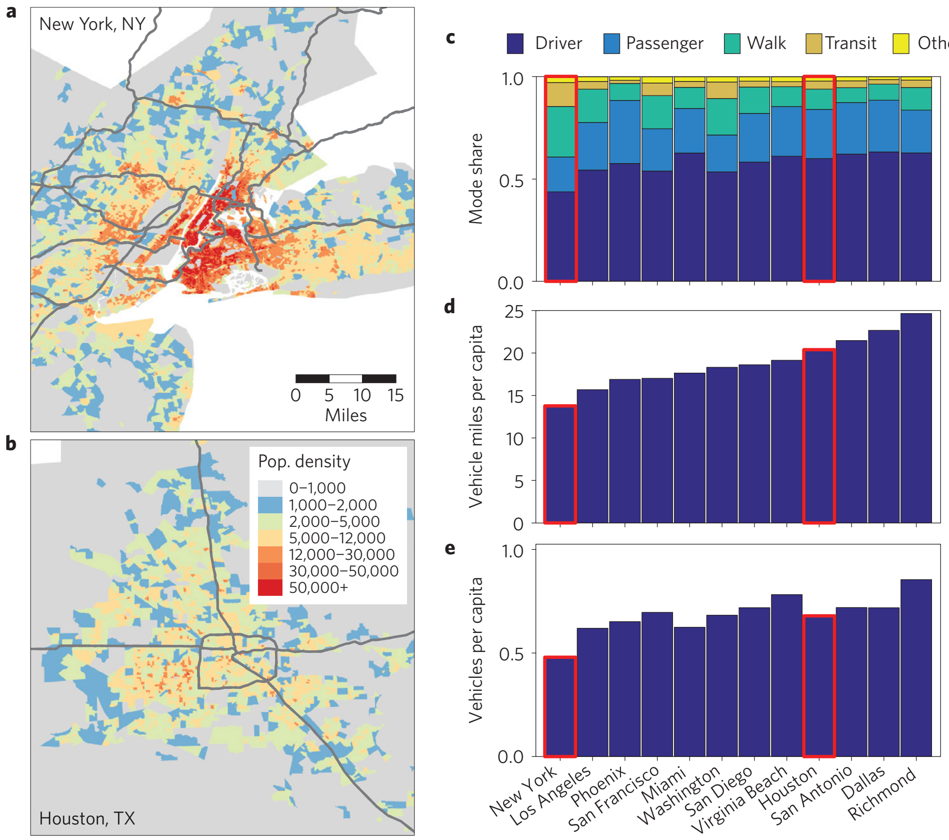

Figure 5 | Differences in travel behaviour and vehicle use across cities. a,b, Population density maps of New York (**a**) and Houston (**b**) (data from ref. 50), displayed in units of people per square mile. **c**, Portion of total trips taken by each mode of transportation. **d**, Vehicles per capita. **e**, Vehicle-days in a year per capita. Red boxes highlight New York and Houston.

Rural areas in aggregate have a DAP and GSP that is below the US average, while urban areas have an above-average DAP and GSP. The aggregate rural DAP is 80.8% and GSP is 52.2%. The average urban DAP across the US is 89.1%, varying from 84–93% in the 12 cities examined in detail (Fig. 3). The average urban GSP is 64.5%, ranging from 58–78% in individual cities. These results support the idea of cities as natural initial markets for BEVs[10,26].

In addition to the DAP and GSP, the average distance and fuel economy of trips is revealing. The rank ordering of cities in terms of DAP and GSP does not individually match that of either distance or fuel economy, as shown in Fig. 3, again illustrating the importance of considering variations in fuel economy in addition to distance in characterizing trip energy requirements.

Variation across cities

The comparison of BEV range constraints applied to individual cities reveals a remarkable degree of similarity in the BEV daily adoption potential across diverse locations, varying from 84% to 93% (Fig. 3 and Supplementary Table 4). This is in contrast to per capita travel energy consumption, which varies by a factor of 1.6 across cities (Fig. 4). These results can be understood by examining the shapes of the energy distributions in individual cities (Fig. 4) and several factors affecting per-capita energy consumption (Fig. 5).

Probability distributions for vehicle-day energy for 12 cities are shown in Fig. 4a. We observe that these functions diverge across cities as vehicle-day energy increases. In other words, the distribution of BEV vehicle-day energy requirements becomes increasingly different across cities as we increase the upper threshold on allowed vehicle-day energy requirements. For an energy threshold defined by the Nissan Leaf's battery capacity, cities appear more similar than they do for a threshold defined by the ARPA-E target[36]. This suggests that while a representative affordable BEV today can be expected to face relatively similar energy requirements across cities, the differences in tail behaviour will cause the mean per-vehicle-day energy use to diverge as battery improvements increase overall DAP towards 100% (Fig. 4a,b).

The factor of 1.6 variation across cities in per-capita energy consumption, shown in Fig. 4b, is explained by several factors. One determinant is the factor of 1.3 variation in daily energy requirements per vehicle (calculated for a BEV). Another important determinant, however, is the difference in the tendency of the population to own and use personal vehicles. Figure 5 shows several statistics capturing this factor. Cities differ considerably in terms of the tendency to use different modes of transport[29], and in the propensity to use personal vehicles on any given day.

Taken together the factors discussed above explain an apparent inconsistency: the significant difference in the per-capita transportation energy consumption and the much more limited difference in the BEV adoption potential across diverse cities. The large variation in energy consumption per capita is explained by some cities relying much less on personal vehicles for travel than others, while the smaller variation in BEV adoption potential is explained by similar energy requirements across cities for those vehicles that are driven. Furthermore, the small number of high-energy trips in the tail affect the mean of the vehicle-day energy distribution but do not greatly affect DAP.

The comparison between New York and Houston provides a striking example of this phenomenon (Fig. 5). By most measures of travel behaviour, New York and Houston are very different cities. Figure 5 shows differences in city layout, transportation mode choice, vehicle ownership, and vehicle use. New York City contains an extensive dense central area, whereas Houston sprawls over a

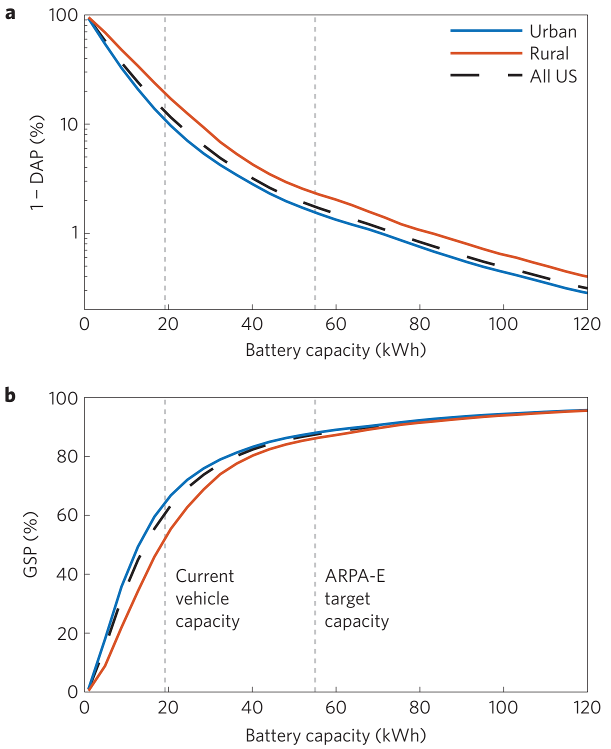

Figure 6 | Effects of increasing battery capacity on BEV range constraints. Battery mass is assumed to be kept constant. **a**, Daily vehicle adoption potential, shown in the inverse to display the decrease of the portion of vehicle-days exceeding one full charge. **b**, GSP, the portion of gasoline use that could be displaced by BEVs given full adoption of within-range vehicle-days. Dotted lines represent usable battery capacity for the 2013 Leaf (left) and for a similar vehicle assuming the ARPA-E specific energy target is reached (right).

similar area at more moderate densities. New York has the highest transit ridership and lowest personal vehicle ridership of all cities in the NHTS, whereas Houston is among the most car-dependent of major US cities. Despite these differences, however, the DAP and GSP for these two cities are remarkably similar, with DAP differing by 1% and GSP by 6%. When vehicles are driven in these two cities, the percentages of vehicle-days served by current BEV technology are strikingly similar. This means that both cities, despite their differences, show substantial BEV adoption potential.

Benefits of battery improvement

How might DAP and GSP increase with improvements to batteries? The vehicle-day energy distributions presented here allow for a quantification of the marginal benefits of improving BEV battery capacity (Fig. 6). Improvements in battery capacity (at constant mass and volume) increase the number of vehicle-days that could be replaced by BEVs, but the results show important nonlinearities. A factor of 2.3 increase in the Leaf's battery specific energy, from its 2013 value of 88 Wh kg^{-1} to the US ARPA-E specific energy target of 200 Wh kg^{-1}, would increase DSP to 98% and GSP to 88%. Further improvements in GSP would require still greater increases in specific energy, with a GSP of 95% requiring an increase in battery specific energy by a factor of six to approximately 420 Wh kg^{-1}. To maintain vehicle affordability and thereby enable widespread BEV adoption, the cost per battery capacity should stay constant or even decrease while battery energy density and specific energy increase. Commercial progress is being made towards this end. For example, the 2017 Chevrolet Bolt BEV is intended to be widely affordable and offers a 60 kWh battery with a specific energy of 138 Wh kg^{-1} (Supplementary Note 1). The 2018 Tesla Model 3 promises comparable range to the Bolt at a similar price point, although with different aesthetics and performance features.

The distinction between urban and rural areas is revealing in this context. While urban areas show a significantly higher GSP than rural areas (52.2% in rural and 64.5% in urban areas on average), the returns to further improvement in batteries are greater in rural areas than urban ones. Increasing battery specific energy and energy density to meet the ARPA-E target would almost eliminate the difference in GSP between urban and rural areas. Batteries with this capacity would allow BEVs to replace approximately 80% of gasoline consumption if fully adopted in both locations.

The relationship between DAP and battery capacity is important to consider in assessing potential long-term limits to BEV adoption. The sub-linearity of DAP versus battery capacity suggests that a complete daily electrification of personal vehicles presents a significant technical challenge, and that other powertrain technologies will be needed for some time even as batteries and charging infrastructure advance.

Discussion

Our results show that current, affordable BEV technology is able to replace 87% of vehicles driven on a given day without recharging. This would allow for a reduction of gasoline consumption by approximately 60%. These findings support the concept that cities are especially suited for early BEV adoption[10,26], given that nearly all cities studied rated as well or better than the national average in two metrics of BEV performance (DAP and GSP). However, we show quantitatively that a substantial portion of vehicle-days, and a larger portion of gasoline consumption, could not be replaced by the modelled BEV. These vehicle-days tend to involve longer travel distances and higher-speed driving, and they tend to be more common for residents of rural rather than urban areas.

These results provide fundamental insight into travel behaviour in cities, adding to regularities that have previously been identified in behaviour and energy consumption in cities[40,41]. We find that daily energy consumption is distributed remarkably similarly across cities for the majority of vehicles and, as a result, diverse cities have similar BEV adoption potential. A small portion of vehicle-days that have particularly high energy requirements do vary in frequency and intensity across cities, and these days cause a disproportionate amount of the variation between individual cities when all vehicle-days are considered. Further, a major factor in the differences between cities is how likely someone is to drive on any given day. These factors together give rise to differences in the per-capita energy consumption across cities.

Increasing BEV battery capacity will allow for greater DAP and GSP, and our results enable the assessment of this potential against climate policy targets, under current and future improved battery performance. For example, meeting existing policy targets would require a reduction of transportation sector emissions of 26–28% from 2005 levels by 2025[1,3]. Even considering the current electric grid mix[42], today's BEV technology is capable of meeting this target. Achieving the GSP for current BEV technology by 2025 would yield an estimated 29% reduction (Fig. 3) from 2005 emissions levels (based on an average US electricity carbon intensity and 0.92% yearly increase in vehicle miles travelled[43], see Supplementary Note 4 and Supplementary Table 5).

Transportation emissions reduction targets for later years may be more ambitious, for example reaching 56% and 80% below 1990 emissions levels by 2040 and 2050[44–46]. Given current battery capacity, modelled after the 2013 Nissan Leaf, carbon emissions from the remaining gasoline vehicles would be enough to exceed the 2040 target, meaning current technology could not provide enough reductions even with entirely carbon-free electricity. However, the Leaf with 55 kWh usable battery capacity (meeting the ARPA-E target battery specific energy of 200 Wh kg^{-1}; ref. 36) could enable nearly full BEV adoption without confronting range constraints (DAP = 98.3%) and could meet the 2040 target in tandem with a 44% reduction in the average carbon intensity of electricity. By 2050, even with complete electrification of transportation, meeting the 80% emissions reduction target would require a reduction of 65% in grid emissions intensity. These examples of rough calculations demonstrate the power of the model for assessing battery technology and electricity CO_2eq emissions intensity against climate policy targets.

The results presented here represent theoretically achievable values of DAP and GSP given BEV range constraints. Realizing these levels of BEV adoption would require that prospective BEV owners have access to personally-operated or other vehicles with longer range that can meet their needs on all days, including high-energy ones[24]. Even with substantial battery improvements, other powertrain technologies may be needed to cover those days with the highest energy consumption. This need may persist for some time, even with expanded (and improved[17,47,48]) charging infrastructure. Predicting high-energy days and providing convenient solutions—such as commercial programmes for sharing internal combustion engine vehicles to complement within-household car sharing and alternative transportation modes—may therefore be critical for increasing BEV ownership.

Many other considerations will also affect realized adoption levels, including consumer preferences for vehicles, and financing options to offset the higher purchase price of BEVs[21,31], as well changes to travel demand over time. These factors will also be important to consider in evaluating BEV technology and transportation policy to achieve emissions reductions.

Methods

General approach. The TripEnergy model draws on information contained in travel data with varying resolution and coverage, as well as data on ambient temperatures. This information is used in a travel demand component and then a vehicle energy component to determine the trip-by-trip energy requirements of travel across the United States. We describe TripEnergy and the methods used in this paper here, and provide further information in Supplementary Note 2.

Data. Data inputs include information on travel behaviour and ambient temperature. We use two sources of data to estimate trip velocity profiles: the National Household and Transportation Survey (NHTS) and GPS data sets from several US cities. The 2009 NHTS[2] contains approximately 1.1 million trips from 150,000 households. The GPS data (Supplementary Note 1) contain speed histories of approximately 120,000 trips from nine cities across the US. Considering both of these data sets provides information on both the travel behaviour of drivers across the US and on representative high-resolution velocity profiles. The representative nature of the GPS drive cycles has been validated as described in Supplementary Note 3.

Vehicle model. To produce the energy distributions used in this paper, we model both vehicle performance and driving demand to determine personal vehicle energy consumption. For the vehicle performance aspect of our model, we estimate tractive energy requirements and the internal efficiency of a given velocity profile, the former using EPA test dynamometer coefficients and the latter using CAFE test results and a method based on ref. 49 (see Supplementary Note 2 and Supplementary Figs 7 and 8 for further discussion). To estimate the amount of auxiliary energy used, we use the National Solar Radiation Database's Typical Meteorological Year database[32] to produce a distribution of possible ambient temperatures for the trip based on its time of day, month and location, which is converted to climate control auxiliary energy consumption via a simple energy balance model. The model uses factory-rated battery capacity estimates, and does not consider consumer-reported deviations from these values due to battery degradation over time.

Demand model. We base overall travel demand in our model on the NHTS, using a de-rounding algorithm (see Supplementary Note 2 and Supplementary Figs 4 and 5) to remove rounding biases from the self-reported data. As the NHTS does not contain high-resolution vehicle speed data, we use a conditional bootstrap procedure to probabilistically match each NHTS trip with a representative set of possible GPS velocity histories. A sample application of this process is shown in Fig. 1. The tractive energy from the vehicle model and the auxiliary energy from the climate model are combined to produce a probability distribution of the energy needs of the NHTS trips.

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Author contributions
J.E.T. designed the study; J.M., M.T.C., Z.A.N. and J.E.T. built the model; Z.A.N., M.T.C., J.M. and J.E.T. performed the analysis; J.E.T., Z.A.N. and J.M. wrote the paper.

Additional information
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Competing interests
The authors declare no competing financial interests.