Off-grid solar photovoltaic systems for rural electrification and emissions mitigation in India

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Over one billion people lack access to electricity and many of them in rural areas far from existing infrastructure. Off-grid systems can provide an alternative to extending the grid network and using renewable energy, for example solar photovoltaics (PV) and battery storage, can mitigate greenhouse gas emissions from electricity that would otherwise come from fossil fuel sources. This paper presents a model capable of comparing several mature and emerging PV technologies for rural electrification with diesel generation and grid extension for locations in India in terms of both the levelised cost and lifecycle emissions intensity of electricity. The levelised cost of used electricity, ranging from $0.46-1.20/kWh, and greenhouse gas emissions are highly dependent on the PV technology chosen, with battery storage contributing significantly to both metrics. The conditions under which PV and storage becomes more favourable than grid extension are calculated and hybrid systems of PV, storage and diesel generation are evaluated. Analysis of expected price evolutions suggest that the most cost-effective hybrid systems will be dominated by PV generation around 2018.

1. Introduction

Developing countries with ambitions both to expand access to electric power and to meet national and international carbon emissions targets need to consider the emissions implications of alternative development pathways[1]. Such countries may also benefit from the opportunity to adopt more innovative energy technologies than developed nations, whose energy economy may already be 'locked in' to conventional, and typically high carbon, power sources.

Diesel generators are a common source of off-grid electricity as they provide low-cost power[2] but with a high carbon intensity[3]. Connection to an electricity grid is often aspired to, allowing flexibility in the power mix and avoiding the need for energy storage, but requires expensive and energy-intensive infrastructure, is slow to reach remote areas and suffers poor reliability in such regions[4, 5]. Renewable sources offer the lowest carbon intensity of generated power but suffer from varying availability and high initial costs, with intermittency in supply leading to the need for storage.

Solar photovoltaics (PV) is the most universally available of the renewables but normally engenders the highest price of electricity. The historically high costs of crystalline silicon based PV have stimulated the development of alternative PV technologies with lower production costs[6], some of these still pre-commercial[7], and others with higher efficiency[8]. These alternatives may be appropriate solutions for the limited capital environment of developing countries but the lack of operational and production experience makes their actual cost and carbon intensity uncertain. Moreover, the relationship between cost, emissions and useful energy for any renewable power source is strongly influenced by the availability of the resource and the demand patterns at the point of energy use.

In planning energy development pathways, policy makers and technology developers need to consider a number of factors. These include the life-cycle cost and emissions of the possible solutions (for example diesel, grid extension and renewables) and combinations thereof, the distance to the grid, the renewable resource, the demand profile and how well it matches the generation profile, and finance models. Such factors are particularly important in the evaluation of new technologies in comparison with the incumbents. Whilst previous studies have addressed the performance[9-11], cost[12-17], and carbon intensity[14, 18] of PV electricity, sometimes in an off-grid context[19, 20], few combine all three[21-25] and none encompass emerging PV technologies. In particular, no previous approaches have addressed mitigation potential from a whole system life-cycle perspective, including storage and accounting for the electricity actually used to satisfy demand.

Here we present a model that combines the levelised cost of used electricity (LCUE), emissions intensity and marginal abatement cost (MAC) of PV power for village electrification, incorporating the options of emerging and established PV technologies in comparison with diesel power and grid extension. We use LCUE as the primary metric of performance as it incorporates issues of mismatch between supply and demand that the levelised cost of generated electricity (LCGE) does not.

The model is applied to locations in rural India, as the country is particularly relevant given its large rural population without electricity[13, 26], its rate of economic development, its commitment to emissions reductions of 20-25% in the carbon intensity of its GDP by 2020 relative to 2005 and its national commitment to solar PV. This is embodied in the Jawaharlal Nehru National Solar Mission which targets 20 GW_p of solar PV capacity by 2022, of which 2 GW is expected to be off-grid[27]. Recent announcements by the Indian government suggest this could be extended further, to a 100 GW_p target by the same year[28]. Despite its growth and emissions targets, India's current reliance on imported diesel for off-grid generation is undesirable from economic, emissions mitigation and health perspectives.

We focus on off-grid systems for this first demonstration of the model because off-grid PV is expected to be an important option for more remote locations, it is compatible with subsequent grid extension and it allows direct comparison of technologies within a closed system[29]. Furthermore, the cost and emissions impact of off-grid solar PV act as upper bounds for solar PV in general. In contrast to previous models we have included full life-cycle cost and emission analysis of both existing and pre-commercial PV technologies. Modelling emerging technologies in this way enables critical production or design issues that influence relative cost and emissions intensity to be identified and optimised prior to finalisation of the production route.

The model, although applied here to small standalone PV systems, can readily be extended to other technologies, regions and application contexts. The approach may be useful to policy makers in assessing the economic and policy case for technology deployment because, as we demonstrate below, the LCUE and MAC of renewables are strongly situation dependent.

2. Methods

2.1 Scenario and data

In modelling the off-grid PV system, we consider a village mini-grid comprising PV generator, battery storage and low voltage distribution network. We examine four PV technologies at different stages of maturity: monocrystalline silicon (c-Si, mature), cadmium telluride thin-film (CdTe, maturing), concentrator PV (CPV, emerging), and organic PV (OPV, pre-commercial). We also investigate future scenarios in which the costs and embedded energy of OPV reduce dramatically[30-32] as a result of manufacturing innovations such as roll-to-roll processing[7].

The scarcity of reliable production and field performance data for emerging technologies, especially in the context of rural electrification, means that the data used and results presented should be viewed with appropriate caution. For OPV, the current case is based on devices demonstrated with a large-scale installation[33]; the costs are derived from the corresponding technological parameters applied to upscaling manufacturing scenarios[32] and is applicable to deployment in the near-term. Owing to the rapid progress being made in the field of OPV these form a representative estimate of current deployable devices based on the available literature, but with improvements in efficiency, lifetime and stability being reported the performance of the technology is consistently increasing. For this reason we also present the future OPV case, representing the long-term potential of the technology, which uses lifetime and efficiency data predicted for improved devices manufactured at the industrial scale[31, 32]. Both the present and future OPV cases consider roll-to-roll processed ITO-free devices to reduce the cost and environmental impact[30]. For comparability to mature technologies the costs of materials and labour for balance of systems and installation are assumed to be the same, although innovative mounting structures made possible from the roll-to-roll production of OPV could reduce the price and embedded energy in the future[33].

Data in this investigation is given in Tables 1-3, which also include assumptions of performance degradation rates and balance of system costs[34, 35]. For production of system components in China we assume specific emissions of 1000gCO_2/kWh and 450gCO_2/kWh for electricity and thermal energy production respectively[26], and 788gCO_2/kWh for that of the Indian electricity grid[36].

Table 1 Key specifications and costs of PV technologies considered, a: including tracker cost.

Parameter	c-Si	CPV	OPV	OPV (Future)	CdTe
Efficiency (%)	16.0[37]	30.0[38]	2.0[30, 33]	7.0[39]	11.9[37]
Degradation (% p.a.)	1.0	0.5	4.0	2.0	1.0
Cost (Wp)	$0.89[40]	$1.60[38] [a]	$1.40[32]	$0.15[31, 32]	$0.75[42]
Installation (Wp)	$0.51	$0.77	$0.51	$0.51	$0.51
Operation and Maintenance (% Total Cost)	0.5	2.0	0.5	0.5	0.5
Energy Meter (Wp)	$0.04				
Inverter (Wp)	$0.55				
Charge Controller (Wp)	$0.21				

Table 2 Manufacturing energy input breakdown of the PV technologies considered. Data from a: de Wild-Scholten (2013), b: Peharz (2005), c: Espinosa (2012) and d: Mason (2006).

<table>
<tr><th>Embedded Energy (MJ/Wp)</th><th>c-Si</th><th>CPV</th><th>OPV</th><th>OPV (Future)</th><th>CdTe</th></tr>
<tr><td>Cell (electrical)</td><td>10.74[a]</td><td>1.30[b]</td><td>2.03[c]</td><td>0.33[c]</td><td>-[a]</td></tr>
<tr><td>Cell (thermal)</td><td>16.73[a]</td><td>1.91[b]</td><td>1.94[c]</td><td>0.31[c]</td><td>6.26[a]</td></tr>
<tr><td>Array Support</td><td>0.82[a]</td><td rowspan="2">8.03[b]</td><td>-[a]</td><td>-[a]</td><td>-[a]</td></tr>
<tr><td>Frame</td><td>1.01[a]</td><td>8.90[a]</td><td>2.54[a]</td><td>1.49[a]</td></tr>
<tr><td>Cables</td><td rowspan="2">0.08[a]</td><td rowspan="3">0.80[b]</td><td rowspan="2">0.11[a]</td><td rowspan="2">0.11[a]</td><td rowspan="2">0.11[a]</td></tr>
<tr><td>Interconnection</td></tr>
<tr><td>Inverter</td><td>2.29[a]</td><td>2.29[a]</td><td>2.29[a]</td><td>2.29[a]</td></tr>
<tr><td>Installation</td><td>0.22[d]</td><td>0.05[b]</td><td>0.24[d]</td><td>0.24[d]</td><td>0.24[d]</td></tr>
<tr><td>Operation and Maintenance</td><td>0.08[d]</td><td>0.09[d]</td><td>0.09[d]</td><td>0.09[d]</td><td>0.09[d]</td></tr>
<tr><td colspan="6"></td></tr>
<tr><td>Total</td><td>31.97</td><td>12.18</td><td>15.60</td><td>5.91</td><td>10.48</td></tr>
</table>

Table 3 Cost and emissions data for battery storage, grid extension and diesel generation. a) The emissions factor of lithium-ion batteries is converted to an emissions intensity using the primary energy conversion factor and emissions intensity of the local grid network.

Electricity Source	Cost	Emissions
Lithium-ion battery cost	\$350/kWh[43, 44]	550 MJ/kWh[a] [45, 46]
Grid extension (plains)	\$2030/km[13]	15.5 tCO_2eq/km[47]
Grid extension (mountains)	\$4600/km[13]	
Diesel fuel cost	\$0.67/litre[48]	1056 gCO_2eq/kWh[49]
Diesel Generator	\$300/kW[50]	

We consider lithium-ion battery storage technology as significant cost decreases and performance improvements are expected in the future[43]; this could drive the replacement of the incumbent lead-acid batteries that are currently more commonly deployed. For a given PV array size, battery capacity and demand profile the model calculates the net present value (NPV) of the system, the levelised cost of used and generated electricity (LCUE and LCGE), the shortfall of unmet demand, the lifecycle specific emissions and, combined with corresponding data for grid and diesel, a marginal abatement cost (MAC). The LCUE is more useful than LCGE when considering off-grid systems since, particularly for PV and battery systems, excess energy is often generated and dumped which has no value to the end consumers[22]. By considering primarily the LCUE it allows an accurate cost of electricity to be considered and favours well-optimised systems. We use the model to investigate the effect of solar irradiance level, topography (which influences the costs of grid extension) and demand profile on costs and mitigation potential. We consider three locations representative of high average irradiance with hilly topography (Ladakh, average GHI = 5.51 kWh/m^2/day), high average irradiance with plain topography (Barmer, average GHI = 5.88 kWh/m^2/day) and low average irradiance with hilly topography (Dhemaji, average GHI = 4.41 kWh/m^2/day). The locations of these sites in India are displayed in Figure 1. For the analysis presented in this paper we consider a hypothetical village located in each area, with 500 inhabitants and a population density of 1000 inhabitants km^{-2}. We consider two demand profiles, namely 'lighting and basic services' (L) and 'income-generating activities' (I), shown in Figure 2. Demand profile L represents the basic electricity demands of newly electrified villages assuming a demand dominated by lighting and is concentrated in hours of darkness. Demand profile I represents a community with additional significant use during the daylight hours for commercial and industrial activity. The 'Baseline' scenario consists of demand profile L being used in Ladakh, which was chosen because of its relatively high irradiance and remoteness.

Figure 1 Map of northern India showing the three considered locations (Ladakh, blue; Barmer, red; and Dhemaji, green) and the capital (New Delhi, gold star).

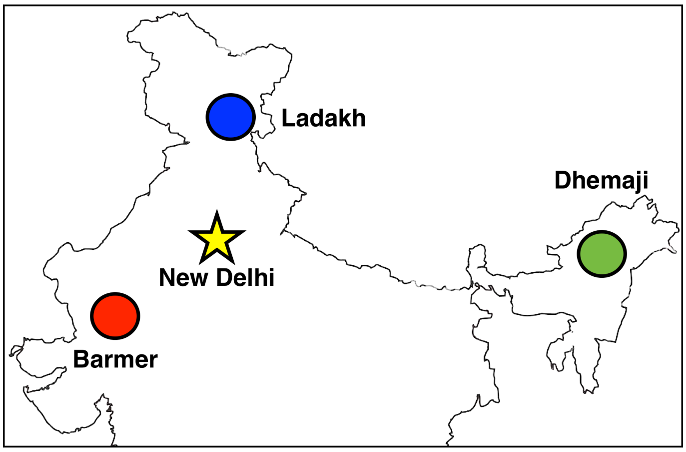
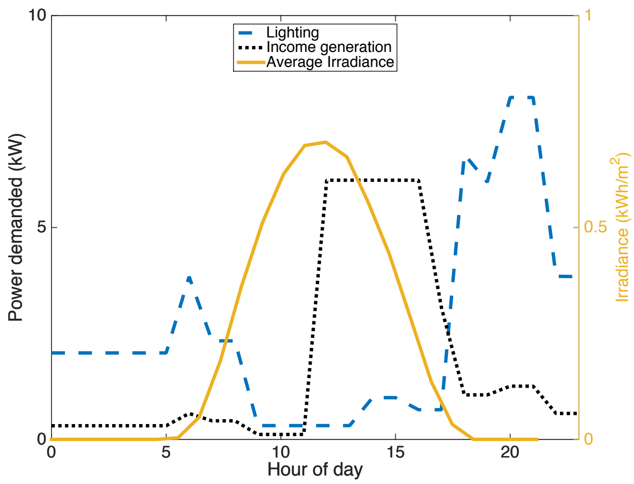


Figure 2 Demand profiles for basic services (L) and income generation (I) and a typical irradiance profile. Demand profile L is greatest during the hours of darkness as it is dominated by the need for lighting, whilst profile I features a heavy load throughout the working day.



2.2 Description of the model

Our model optimises the PV and storage system size in a given location for a given application and calculates the net present value (NPV), LCUE and lifecycle specific emissions of the system using the data given in Tables 1-3. Here, we optimise for LCUE, but optimising to other variables is possible. At the start of the simulation we select a PV technology, a battery technology and specify the demand profile representing the application. The model uses location-specific hourly irradiance data from the NREL SUNY dataset[51] and converts this into energy generated by the chosen PV technology, accounting for conversion efficiency. A range of PV and storage system sizes are considered and a 20-year project period is simulated with hourly time-steps. Generated energy is used directly to meet demand where possible with excess energy stored in the battery until the battery is charged, after which it is dumped. When there is a deficit of generated energy, the battery is used to meet demand until it is empty. In this way, the state-of-charge of the battery is tracked hourly. The model accounts for losses due to inefficiencies in the battery, charge controller and inverter. The battery is subject to degradation over its lifetime based on the number of cycles and depth of discharge it experiences and is replaced if its capacity drops below 60% of its original value[45, 46, 52]. After 20 years, the simulation ends and the model calculates the shortfall between supplied and generated electricity over the lifetime of the system. Further description of the model is available in the Supplementary Information.

The model calculates the NPV of the system over the simulation period (N = 20 years), considering system component costs, operation and maintenance costs, and a capital financing rate r (Equation 1). For the simulations presented here, we assume costs are discounted annually at 11.5%, representative of rural regional bank lending. System component costs include the cost of the initial system installed C (including construction of the village mini-grid) and replacement costs $C^{(n)}$ in year n for the inverter (every 10 years), modules (every 5 or 10 years, relevant for OPV only) and replacement of batteries once their capacity drops below 60% of their rated capacity. Levelised cost of electricity (LCOE) is calculated as in Equation 2, with E_{disc} representing the used or generated electricity for the cases of LCUE and LCGE respectively. The lifecycle emissions ε of the system in supplying the total electricity E is determined, yielding the specific emissions (Equation 3) and the model further calculates the MAC (Equation 4) of each solar PV technology by comparing the LCUE and emissions intensity of the minigrid to the counterfactual (CF) cases of grid extension and diesel generation.

$$NPV = C_{PV} + C_{Install} + C_{Network} + \sum_{n}^{N} \frac{C_{PV}^{(n)} + C_{Storage}^{(n)} + C_{Inverter}^{(n)} + C_{O\&M}^{(n)} + C_{BOS}^{(n)}}{(1+r)^n} \quad (1)$$

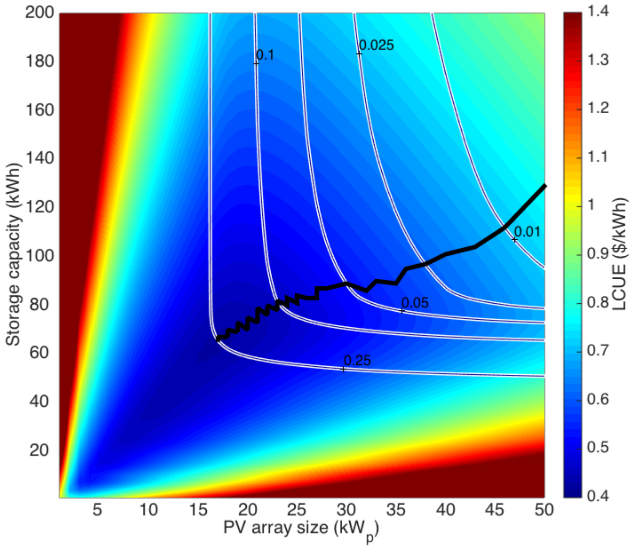
$$LCOE\ (\$/kW\,h) = \frac{NPV}{E_{disc}} \quad (2)$$

$$Specific\ Emissions\ (gCO_2eq/kWh) = \frac{\varepsilon_{Total}}{E_{used}} \quad (3)$$

$$MAC\ (\$/gCO_2eq) = \frac{NPV_{PV} - NPV_{CF}}{\varepsilon_{CF} - \varepsilon_{PV}} \quad (4)$$

Figure 3 shows the LCUE of a range of PV and storage system sizes, for the example of c-Si and lithium-ion storage, overlaid with white curves of constant shortfall. There are many possible combinations of PV and storage which yield the same proportion of demand being met, but the LCUE of these systems varies significantly. The black curve identifies the system with the lowest LCUE for a given shortfall and highlights it as the optimum. For this research, a shortfall of 5% was used to evaluate the NPV, LCUE and emissions intensity of the mini-grid systems as this eliminates the most extreme instances of low generation and high demand, but is still sufficient for the vast majority of the time.

Figure 3 LCUE (colour bar) for a range of system sizes using c-Si and lithium-ion battery technology. White lines are of contours of equal shortfall and the black line denotes the optimum system for a given shortfall.



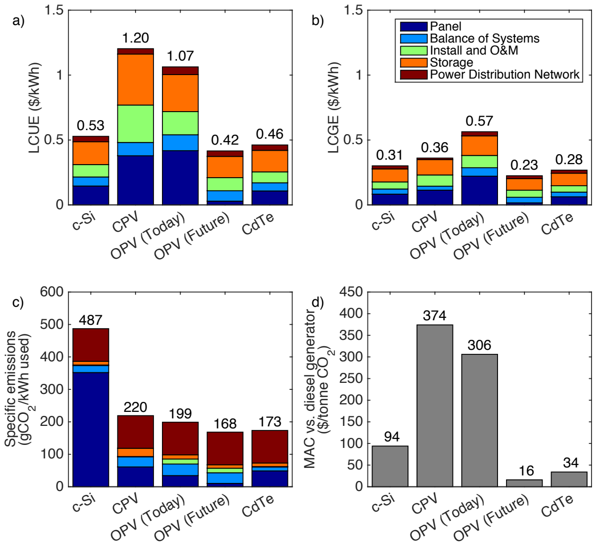
The corresponding LCUE and specific emissions values for grid extension are derived using data from the literature concerning the cost and emissions of grid electricity and those associated with extending the distribution network[29, 53]. Data concerning the distribution network is taken from Nouni (2008)[13], and hence we consider two values corresponding to 'plain' and 'hilly' topography. The specific emissions value for diesel generation is taken from the literature and the cost is calculated using literature data[49] and current diesel prices in India[50, 54]. Table 3 shows the key data used for grid extension and diesel generation.

3. Results and Discussion

3.1 Performance of different PV technologies

Figures 4a and 4b show the LCUE and LCGE values for electricity used and electricity generated respectively in the Baseline scenario, corresponding to the hilly region of Ladakh with high insolation and using demand profile L, for each PV technology with lithium-ion storage. At current prices, an LCUE of between \$0.46-\$1.20/kWh used can be achieved dependent on the PV technology chosen. Due to the relatively poor mismatch between the times of irradiance (and therefore generation) and demand (shown in Figure 2) 'dumping' of excess energy, ranging from 42% to 70% of the total generated, occurs during the day. This leads to the requirement for a large storage capacity to shift energy supply from daytime to evening. With its current high cost, storage accounts for a significant proportion of the total LCUE.

Figure 4 a) LCUE and **b)** LCGE for the optimum PV-storage system for each of the technologies with lithium-ion battery storage and demand profile L. Owing to the mismatch between times of irradiance and demand, the price of used electricity is inflated compared to the price of generation, but better represents the cost to consumers. **c)** The specific emissions of the PV-storage systems. The energy used in manufacturing panels has a significant impact; energy-intensive panel production leads to c-Si having the greatest carbon intensity. **d)** The MAC of a PV-storage system as an alternative to diesel generation.



Whilst the other technologies utilise both direct normal and diffuse irradiance, CPV utilises only direct normal irradiance and hence performs poorly under cloud cover; this intermittency leads to it having the highest LCUE. The system must be oversized to compensate for its reduced access to suitable solar resource, particularly the battery storage, and the majority of its generated energy is dumped since the system only works at full capacity during the times when the solar resource is lowest.

OPV also has a relatively high cost, in this case due largely to the cost of modules which must be replaced every five years following current estimates of lifetime. As the OPV (Future) case shows, the LCUE for OPV could be reduced to levels comparable with c-Si and CdTe if the module prices decrease despite inferior module lifetimes. C-Si shows a slightly higher LCUE than CdTe owing to higher module costs. The cost of the power distribution network makes a small contribution to LCUE in the modelled scenario, however this would increase for a population density lower than 1000 inhabitants km^{-2}.

As Figure 4c shows, the energy intensity of module production is a major factor in the total system specific emissions. CdTe currently has the lowest carbon intensity of 173 gCO_2eq/kWh, and c-Si shows the highest carbon intensity at 487gCO_2eq/kWh. Despite the low carbon intensity in a single OPV module, the need for module replacement every five years assumed here leads to large emissions from module production and balance of systems. As OPV is a pre-commercial technology and efficiencies and lifetimes are still improving, the actual costs and emission intensities could prove lower in practice; the OPV (Future) case results in lower emissions. CPV benefits from reduced cell emissions owing to its small area of photoactive material, however the use of glass and steel in the tracker increases the total module emissions to 220 gCO_2eq/kWh, comparable to other technologies. Again, as CPV is an emerging technology with limited operational experience, the costs and emission intensity may yet decrease. The high carbon intensity of current dominant technology, c-Si at 487 gCO_2eq/kWh, could represent a concern for system designers motivated by reducing emissions and may suggest a change to a lower-carbon option is necessary. In contrast to its small contribution to LCUE, the power distribution network contributes a large fraction of the specific emissions for all technologies as a result of the energy-intensive manufacture of the copper conductors.

Perovskite solar cells have attracted significant attention owing to their high and rapidly increasing performance efficiencies. Despite not yet reaching a manufacturing stage suitable for deployment[55], an estimate of their current state in comparison to other technologies can be made. Using manufacturing costs similar to those for present OPV[31, 32] and lifetime and performance assumptions from recent LCA studies[56-58] the LCUE is found to be prohibitively high ($2.62/kWh) for lifetimes of one year. If manufacturing processes can be improved and lifetimes can be extended to five years the LCUE falls to $0.74/kWh, similar to current technologies. Furthermore, if the transition from lab-scale to commercial production results in a reduction of embedded energy comparable to that which OPV experienced [30, 59], the carbon intensity of the system falls to 270 gCO_{2eq}/kWh. An increase in the scale of manufacture of perovskite cells could provide the opportunity for this emerging technology to be used in applications such as this.

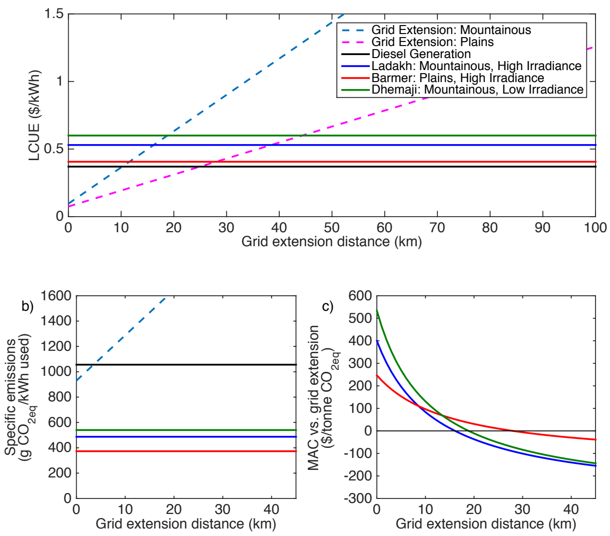
This comparison shows that the choice of PV technology affects both LCUE and carbon intensity and, importantly, that the two are not closely correlated. At present, LCUE is likely to be the primary driver of technology selection. In a scenario where emissions are priced highly or the cost of materials and processes reflect the embedded energy more closely, the variation in specific emissions may have a significant effect on technology choice. As the LCUE and carbon intensity of the various technologies develop at different rates, for example through innovation or scale-up, it will be important to account for both metrics when evaluating technologies in the context of climate change mitigation. One possibility is to use the marginal abatement cost (MAC), which measures the cost per tonne of CO_2 avoided relative to an alternative (carbon-intensive) technology.

Figure 4d shows the MAC of each PV technology relative to diesel generation, using a diesel cost of $0.67/litre[48, 54] and a diesel emissions factor of 1056 gCO_2eq/kWh[49]. MAC is calculated from Equation 4. The low cost and emissions intensity of CdTe lead to it having the lowest MAC of $34/$tCO_2$, significantly less that of CPV at $374/$tCO_2$. The MAC of OPV could be significantly reduced from $306/$tCO_2$ to just $16/$tCO_2$ if the embedded energy of the modules can be lowered as in the case of OPV (Future). The low LCUE of c-Si means that its MAC is also relatively low at $94/$tCO_2$: this is a result of the fact that despite being the most emissions-intensive PV option, it still has a far lower environmental impact than diesel generation.

3.2 Comparison to grid extension

In the following scenarios we focus for clarity on c-Si, currently the dominant technology in India and worldwide and with accurately known costs and carbon intensities. First, we consider the three locations (Ladakh, Barmer and Dhemaji), and compare the LCUE and carbon intensities of off-grid PV and storage with those of grid extension and diesel generation. Figure 5a shows the LCUE of each of the electricity supply options in the three locations as a function of distance from the existing grid. The LCUE of off-grid PV and diesel are independent of distance to the grid, whilst the LCUE of grid extension depends both on the distance from the grid and on the local topography[13]. We take an LCUE of $0.05/kWh for grid electricity at zero grid extension distance[60]. The cost of diesel generation is calculated using a price of $0.67/litre[48, 54] and incorporating capital and O&M costs, giving an LCUE of $0.37/kWh when supplying 100% of demand.

Figure 5 a) LCUE, **b)** specific emissions and **c)** MAC of c-Si and lithium-ion storage systems in three different locations as a function of distance to the electricity grid. Breakeven distances show the scenarios when it is favourable to deploy different technologies, the main factor of which is the local topography.



The dependence of grid electricity cost on both extension distance and topography is far more significant than the dependence of PV LCUE on irradiance. The breakeven distance, after which off-grid PV has a lower LCUE than grid extension, is similar for the two hilly locations with high or low irradiance levels (Ladakh and Dhemaji) at distances greater than 16 km and 19 km respectively. This is similar to breakeven distances for biomass and PV systems from previous studies[29, 53]. For the plains location, Barmer, with high irradiance it is much larger, with the off-grid PV being the cheaper option for distances greater than 28 km. Furthermore, it can be seen that the LCUE of hilly locations ($0.53/kWh and $0.60/kWh) are more similar to each other than that of the plains location ($0.41/kWh). This is likely to be due to the larger seasonal variation in irradiance in Ladakh, which results in the off-grid PV system being limited by the lower irradiance conditions in winter in the absence of seasonal energy storage. Whilst the LCUE of diesel generation makes it the cheapest option in the mountainous locations, and equal to PV generation in the plains location, Figure 5a shows that the cost of grid extension is expensive in comparison to PV systems, particularly in hilly regions. Purely in economic terms, the distance from the grid (over a range of tens of kilometres) is the single most important consideration in choosing locations for deployment of off-grid PV for useful electricity generation.

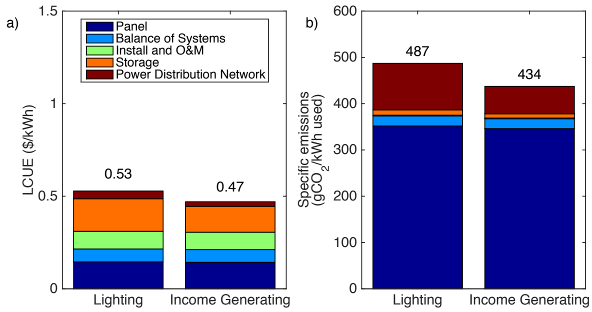
Figure 5b shows the carbon intensity of the same technology options as a function of grid extension distance. It can be seen that the carbon intensity of off-grid PV in all locations (373-540gCO_2/kWh) is lower than that of the grid for all grid extension distances (930gCO_2/kWh or higher), and lower than that of diesel generation (1056 gCO_2/kWh). As with LCUE, grid extension distance is a more important driver of carbon intensity than location and solar irradiance level. Figures 5a and 5b therefore show that off-grid PV is the lowest emissions technology option in all cases, with minimum emissions savings of at least 516gCO_2/kWh versus diesel generation and 390gCO_2/kWh versus grid extension, and potentially much greater savings for larger grid extension distances.

Figure 5c shows the sensitivity of the MAC to distance from the grid, ranging from -\$150/tCO_2 for the most remote locations to almost \$540/tCO_2 for those within 10km of existing infrastructure. As before, the local irradiance is less significant than the extension distance. This implies that investment in off-grid PV power is already feasible from a financial and climate perspective for communities located further than 19 km and 28 km from the grid, the respective distances for mountainous and plains terrain at which the MAC becomes negative and therefore economically favourable. The introduction of carbon prices would decrease these breakeven distances and therefore increase the number of locations where minigrid deployment would be favoured ahead of grid extension. To reduce overall MAC of PV technologies, the largest impact can be made by reducing the costs of storage rather than the costs of PV panels, although it is still worthwhile extending the lifetime of newer technologies such as OPV and lowering the emissions of production processes.

3.3 Comparison of demand profiles

The current high cost of useable off-grid PV electricity is due mainly to two factors: the need for expensive storage as a result of the mismatch between generation and demand and the dumping of a large fraction of the generated energy. In our Baseline scenario in the hilly, high insolation region of Ladakh using c-Si, 43% of the generated energy is dumped in this way for demand profile L. We study the effect of better matching of generation and demand with the addition of a second demand profile I, corresponding to a similar community at a later stage of economic development with additional daytime demand from commerce and small industry resulting in a daily demand of 106 kWh, compared to 62 kWh for demand profile L (shown in Figure 2). It might be expected that a smaller fraction of electricity would be dumped when significant consumption occurs during the daytime. Figures 6a and 6b displays their LCUE and carbon intensity breakdowns, with demand profile I featuring a reduction of both LCUE and carbon intensity of 11%. Profile I features a lower contribution from the distribution network as the same size network serves a larger demand, but this is offset by contribution from the carbon intensive c-Si PV panels. A closer matching of generation and demand, peaking during the middle of the day and decreasing in the hours of darkness, would lead to further reductions in LCUE and carbon intensity. This demonstrates that knowledge of the application, usage pattern and likely evolution for an off-grid PV power system should not be ignored in an assessment of the MAC associated with deployment of the technology.

Figure 6 a) LCUE and **b)** specific emissions of demand profiles L and I in the baseline scenario. Owing to better demand matching, the income-generating profile sees a reduction in cost and carbon intensity compared to lighting alone.

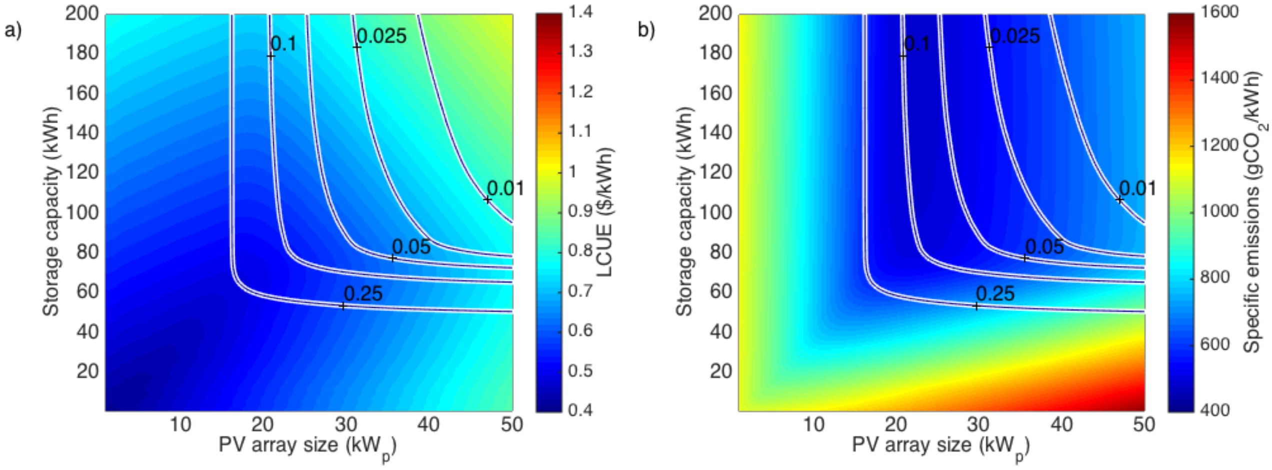


3.4 PV-storage-diesel hybrid system

A pragmatic solution to the poor matching of supply and demand would be to utilise diesel generation to supply electricity when the PV and storage system is unable to. We therefore consider a hybrid system consisting of a PV array, battery storage and a diesel generator that together now satisfy 100% of the minigrid demand. Further details of this process are available in the Supplementary Information.

Figure 7a displays the LCUE of this hybrid system for various combinations of c-Si PV and lithium-ion storage sizes. Analogous to Figure 2, the white lines indicate the shortfall of the given PV and storage systems, which is now being met by diesel generation. Figure 7a shows that at present-day prices the cheapest solution contains a majority contribution from diesel. This is due to the low price of diesel ($0.67/litre) and high price of storage ($350/kWh), which favours small PV and storage systems supplying a small fraction of the demand, with the majority being met by diesel.

Figure 7 a) LCUE and **b)** carbon intensity of a PV-storage-diesel hybrid system using c-Si and lithium-ion batteries meeting 100% of demand. White lines correspond to shortfall from the PV and storage system, which is now met by diesel generation. The cheapest systems rely heavily on diesel power, and are among the most carbon intensive. Increasing the proportion of demand met by PV and storage yields lower specific emissions, provided the systems are correctly sized.



The emissions intensities of the hybrid systems are shown in Figure 7b. The opposite trend is seen with emissions than with LCUE, with systems that rely heavily on diesel generation leading to the highest carbon emissions. In contrast, the system discussed above which meets 95% of the demand through PV and storage, and now uses diesel for the remaining 5%, has an average emissions intensity of 539 gCO_2/kWh, 49% lower than that of diesel alone (1056gCO_2/kWh). Comparable analysis for CdTe hybrid systems can be found in the Supplementary Information.

Figure 7b also highlights the importance of optimising the size of a hybrid system. Despite supplying more of the demand with PV and storage, many system sizes supplying less than 1% of demand from diesel in Figure 7b suffer greater emissions intensities than those using diesel generation for 5-10% of demand. This follows as a consequence of the mismatch between demand and generation which results in oversizing the system, embedding carbon in extra PV and storage in order to meet a comparatively small fraction of demand.

3.5 Future hybrid systems

Currently the low cost of diesel and high cost of storage results in the hybrid system with the lowest LCUE relying predominantly on diesel generation. Diesel costs are expected to increase in the future[61], possibly as a result of phasing out subsidies[62, 63], and innovations in battery technology could both increase storage performance and reduce its cost[43, 44, 64]. Figure 8 shows how these developments would impact the cheapest hybrid system. For a given storage and diesel price, the hybrid system using c-Si PV with the lowest LCUE is selected and the fraction of demand met by diesel and specific emissions of used electricity is plotted. Further detail on this process is available in the Supplementary Information, in addition to a comparable analysis using CdTe.

Figure 8 a) Fraction of demand met by diesel generation and **b)** the resultant specific emissions for the cheapest LCUE system using c-Si at given storage and diesel prices. The possible price evolution is shown for the period 2015-2025 and displays a transition period before 2017 when the cheapest system is not only powered mainly by PV and storage, but also has the lowest specific emissions.

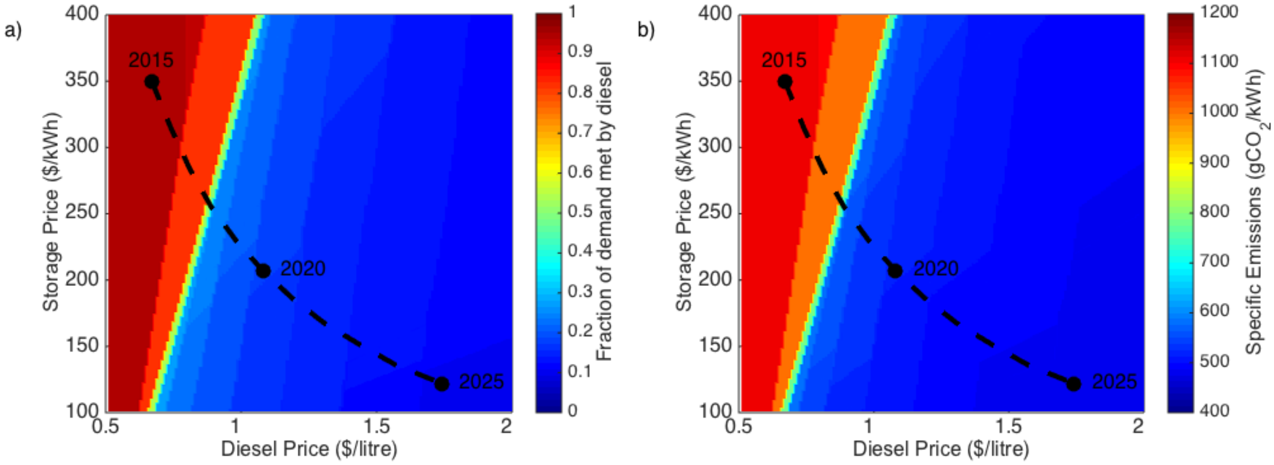


Figure 8a shows that for current costs (marked '2015') the cheapest hybrid system is almost entirely diesel powered, but in the future it is anticipated there will be a sharp transition towards systems that rely on PV and storage to supply over 80% of electricity demand, expected around 2018. This also marks the transition into the region of lowest specific emissions, as shown in Figure 8b.

Hybrid systems dominated by renewable energy are those most resilient to increasing diesel prices, resulting in a lower and more stable LCUE, and highlight the need to correctly optimise the system for its entire usable lifespan. In some regions with high insolation and high diesel costs, such as sub-Saharan Africa, this transition may have already taken place.

4. Conclusions

The model was used to simulate the deployment of off-grid PV and storage systems in three locations in India. By accounting for the costs and performance over a twenty-year lifetime, the LCUE, carbon intensity and MAC compared to diesel of a cost-optimised system were found to be highly dependent on the choice of PV technology. The incumbent technology c-Si was found to have a moderate LCUE but far higher specific emissions than CdTe, which featured the lowest LCUE, specific emissions and MAC compared to diesel generation. Developments in OPV manufacture, such as increasing efficiencies and lifetimes and decreasing costs, could lead to it rivalling CdTe in these areas. CPV performs relatively well with regards to its environmental impact, however its reliance on direct normal irradiance means a significant fraction of its generated energy is dumped, increasing its LCUE. Storage contributes significantly of the total system cost when using mature PV technologies and the expected decrease in cost in this area will reduce the LCUE.

When compared with the extension of an existing electricity grid, topography was more significant than irradiance in determining the cost-effectiveness of PV, which was always the least carbon intensive option even considering only the electricity used. Breakeven distances for grid extension were found to be 19 km and 28 km for hilly and plains locations respectively and MACs as low as -\$150/tCO_2 can be achieved for the most remote locations, areas where it would be most effective to deploy minigrids. Introductions of carbon prices would decrease these distances and therefore increase the number of feasible deployment locations. Demand type was found to have less of an impact on the LCUE than topology, although income-generating demand profiles featured marginally lower LCUE and specific emissions.

In order to meet 100% of demand a hybrid system consisting of a PV array, battery storage and diesel generator was considered. At present the low cost of fuel gives diesel-dominated systems the lowest LCUE but at the greatest emissions cost. The importance of not oversizing the PV array and storage to supply all of the demanded electricity is highlighted as the lowest emissions systems feature diesel generation supplying around 10% of demand. Reductions in storage costs and increasing diesel prices could lead to the cheapest hybrid systems featuring majority renewable generation before 2017.

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