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Forecasting Indonesia's electricity load through 2030 and peak demand reductions from appliance and lighting efficiency

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ABSTRACT

Indonesia's electricity demand is growing rapidly, driven by robust economic growth combined with unprecedented urbanization and industrialization. Energy-efficiency improvements could reduce the country's electricity demand, thus providing monetary savings, greenhouse gas and other pollutant reductions, and improved energy security. Perhaps most importantly, using energy efficiency to lower peak electricity demand could reduce the risk of economically damaging power shortages while freeing up funds that would otherwise be used for power plant construction. We use a novel bottom-up modeling approach to analyze the potential of energy efficiency to reduce Indonesia's electricity demand: the LOAD curve Model (LOADM) combines total national electricity demand for each end use—as modeled by the Bottom-Up Energy Analysis System (BUENAS)—with hourly end-use demand profiles. We find that Indonesia's peak demand may triple between 2010 and 2030 in a business-as-usual case, to 77.3 GW, primarily driven by air conditioning and with important contributions from lighting and refrigerators. However, we also show that appliance and lighting efficiency improvements could hold the peak demand increase to a factor of two, which would avoid 26.5 GW of peak demand in 2030. These results suggest that well-understood programs, such as minimum efficiency performance standards, could save Indonesia tens of billions of dollars in capital costs over the next decade and a half.

Introduction

Indonesia is the largest energy consumer in the Association of Southeast Asian Nations (ASEAN), accounting for more than 36% of the region's energy demand and consuming 66% more energy than the second-largest user, Thailand (IEA (International Energy Agency), 2013). Indonesia's electricity demand is growing rapidly, driven by robust economic growth combined with unprecedented urbanization and industrialization. Indonesia's population was 255.5 million in 2015 (MEMR (Ministry of Energy and Mineral Resources of the Republic of Indonesia), 2016), including an emerging middle class of 88 million people in 2014. The middle class is predicted to grow to 141 million by 2020 (Rastogi, Utama, & Choudhury, 2016). Total electricity demand increased from 134.5 TWh in 2008 to 203 TWh in 2015, an average growth rate of 6% per year (MEMR (Ministry of Energy and Mineral Resources of the Republic of Indonesia), 2016). In response to continued economic and demographic drivers, demand for electricity is projected to rise steadily (MEMR (Ministry of Energy and Mineral Resources of the Republic of Indonesia), 2013).

Electrification of non-electrified households will be one major driver. In 2015, Indonesia's electrification rate was 88.3%, up from less than 68% in 2010 (IEA (International Energy Agency), 2016).[1] However, electrification rates vary significantly across the country's 34 provinces and more than 17,000 islands—particularly between urban and rural regions. Although Jakarta has nearly full electrification, with an electrification rate over 99%, the rates of the far eastern regions of Nusa Tenggara Timur and Papua are just 59% and 43%, respectively (IEA (International Energy Agency), 2016). In addition, many households have unreliable or low-quality access to power in terms of the number of hours of continuous electricity (IEA (International Energy Agency), 2016).

In 2017, the Indonesian Ministry of Energy and Mineral Resources (MEMR) issued the much-anticipated 2017–2026 Electricity Supply Business Plan (Rencana Umum Penyediaan Tenaga Listrik, or RUPTL), which aims to achieve an Indonesian electrification rate of 100% by 2026. To achieve this level of electrification, the RUPTL anticipates that at least 77.9 GW of power plants must be constructed by 2026. The planned 2025 electricity-generation mix is 50.4% coal, 26.7% natural gas (including liquefied natural gas), 9% geothermal, 12.3%

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[1] "Electrification rate" is defined here as the number of households that have been provided with some form of electricity supply divided by the total number of households.

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hydroelectric, 0.4% diesel fuel, and 1.2% other fuels (PLN (Perusahaan Listrik Negara), 2017). This mix is similar to the required mix in the draft 2015–2034 National Electricity Plan (Rencana Umum Ketenagalistrikan Nasional, or RUKN) of approximately 50% coal, 24% natural gas, 25% renewables (revised upward from 23% in July 2015), and 1% diesel fuel by 2025 (MEMR (Ministry of Energy and Mineral Resources of the Republic of Indonesia), 2015a). Constructing this level of power generation will require investment of at least US$110.1 billion (PWC (PricewaterhouseCoopers), 2016a), and an additional US$43.7 billion investment is estimated for expansion of the transmission and distribution networks (PWC (PricewaterhouseCoopers), 2016a).

In mid-2015, President Jokowi Widodo announced an ambitious program to build 35 GW of additional capacity by 2019 to cope mainly with electricity shortages and also reduce the country's dependence on fossil fuels. However, Indonesia's National Energy Board (Dewan Energi Nasional) has reportedly stated that only 19 GW of electricity is likely to be achieved by 2019 (PWC (PricewaterhouseCoopers), 2017). In 2015, about 90% of Indonesian generation came from fossil fuels (56% coal, 25% natural gas, and 9% oil), with the rest coming from hydroelectric (6%) and geothermal (4%) (MEMR (Ministry of Energy and Mineral Resources of the Republic of Indonesia), 2016). Out of the 35 GW planned for 2019, fossil fuels will constitute 92% (56% coal and 36% natural gas), and renewables will constitute 8% (with only 2.5% from wind and geothermal) (PWC (PricewaterhouseCoopers), 2016a). From the government's perspective, coal is considered the quickest, easiest and cheapest way to provide millions of people with electricity. This project is estimated to cost about US$73 billion, including generation, transmission, and distribution investments (PWC (PricewaterhouseCoopers), 2016b).

At the same time, Indonesia has committed—through its Nationally Determined Contribution[2]—to a renewable energy target of 23% by 2025 as well as a 29% unconditional reduction in CO_2 emissions (11% of which, i.e., 314 Million ton CO_2 (Mton CO_2), is from the energy sector) compared with a business-as-usual (BAU) scenario, plus an emissions reduction of up to 41% in 2030 contingent on international support (14% of which, 398 Mton CO_2, is from energy sector) (UNFCC (United Nations Framework Convention on Climate Change), 2016). Under the country's current plans, however, growing fossil fuel generation would increase electric-sector CO_2 emissions dramatically over the next 10 years, and achieving the renewable energy target by 2025 would be a challenge.

For this reason, implementation of energy-efficiency measures is crucial to achieving Indonesia's energy and climate goals. In particular, energy efficiency is needed to slow the growth in peak demand, which the RUKN estimates will otherwise reach 189 GW in 2031. Indonesia's National Energy Conservation Plan (RIKEN) sets sectoral demand-reduction targets: a 15%–30% reduction in the industrial sector (for select industries), 25% reduction in the commercial building sector, and 10%–30% reduction in the residential sector.[3] However, no information about implementing these targets is provided, nor are the targets included in the country's electricity-expansion plans.

This paper provides the technical basis for an energy-efficiency roadmap that would help Indonesia meet its goals sustainably. We analyze the projected peak-load and daily load-curve impacts of energy-efficient appliances and lighting, along with the resulting impacts on future capacity expansion in Indonesia. We also evaluate the CO_2 emissions reductions due to the widespread deployment of energy-efficiency measures.

[2] Per the Paris Agreement under the United Nations Framework Convention on Climate Change.

[3] Electricity demand in Indonesia is largest in the residential sector (44%), followed by the industrial (32%) and commercial (24%) sectors (MEMR (Ministry of Energy and Mineral Resources of the Republic of Indonesia), 2016).

Literature review

Accurate load forecasting can yield substantial cost savings to the electricity sector (Bunn & Farmer, 1982). Numerous studies use load curve forecasting. Some focus on forecasts in the short (day) or medium (week or month) term, mostly to address individual aspects of hourly load projections such as economic power generation, system security, or renewable integration (Khotanzad, Rohani, & Maratukulam, 1998; Santos, Martins, & Pires, 2007; Saini, 2008; González-Romera, Jaramillo-Morán, & Carmona-Fernández, 2008; Pedregal & Trapero, 2010; Cheng-Ting & Chou, 2013; Chitsaz, Shaker, Zareipour, Wood, & Amjady, 2015; Dudek, 2016; Clements, Hurn, & Li, 2016). In contrast, long-term forecasting is used to define annual peak load or global energy that consumers will demand in about 20 years, to schedule expansion planning strategies for production and distribution systems. Although long-term projections of load curves and peak loads are not new to the literature, very few analyses include sector and end-use details. Most of the studies project future capacity but neglect the evolution of peak load, either scaling a historical growth rate according to an assumed future electricity demand (Filik, Gerek, & Kurban, 2011) or generating regression models based on historical characteristics (Aslan, Yavasca, & Yasar, 2011; Sotiropoulos, 2012; Andersen, Larsen, Juul, & Gaardestrup, 2014). Among the other methods employed for long-term forecasting are the Grey forecast method (Niu, Jia, Lv, & Zhang, 2008), Fuzzy inference (Lu, Yao, Huifan, & Qing, 2007), particle swarm optimization (Niu, Li, Li, & Liu, 2009), artificial neural networks (ANNs; Carpinteiro et al., 2007), and support vector regression (Ye, Zhu, & Xiao, 2012). Most of those studies focus on the load curve projection of a region or consumer group. None of them are adequate in the context of long-term energy system modeling, in which new technologies penetrating and existing technologies exiting the market may imply significant change to the future load shape and peak load.

Some studies do, however, focus on individual appliances or events. Koreneff et al. (2009), for example, assess the impact of large-scale diffusion of electric vehicles and heat pumps on future load curves. Evolution of load curves primarily depends on the annual electricity demand and estimated impact of electric vehicles and heat pumps on aggregated national load profiles, which are obtained based on 1000 consumer load data. Hainoun (2009) and Pina, Silva, and Ferrao (2011) determine user-specific load profiles for representative customer groups within the industrial, commercial, and residential sectors, based on empirical data. These profiles are scaled according to an annual electricity demand projection and combined to generate the overall load curve. However, diffusion of new technologies is not explicitly considered in those three studies. Bobmann and Staffell (2015) compare two long-term load forecasting models, eLOAD (Electricity Load Curve Adjustment) and DESSTinEE (Demand for Energy Services, Supply and Transmission in Europe), that can reflect the diffusion of new technologies—including household appliances, heat pumps, heating devices, and electric vehicles—in load curves for Germany and the U.K. The eLOAD model projects the long-term evolution of hourly electricity load curves at the national level for all EU27 countries up to 2050. DESSTinEE is a model of the European energy sector in 2050, which accepts demand for energy services as an input and then models hourly demand and generation profiles. eLOAD considers technology-specific load profiles for all end uses and technologies. However, there appears to be no published eLOAD analysis investigating the impacts of energy-efficient alternatives in the residential and commercial sectors. The DESSTinEE analysis is coarser, using load profiles for each economic sector as a whole, plus profiles for heating technologies and electric vehicles.

Studies of evolving Indonesian peak load and load curves are also scarce. Kuncoro and Dalimi (2007), for example, use an ANN method to forecast long-term peak load in the Java-Bali-Madura electricity system. Gross domestic product (GDP), population, number of households, electrification rate, and electricity consumption by sector represent the “neurons” that would be affecting peak growth. Their results indicate

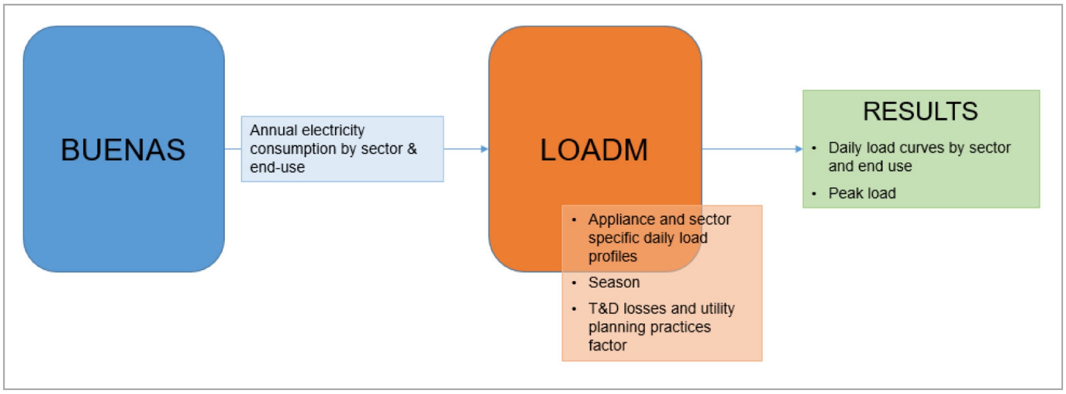

Fig. 1. Schematic relationship between BUENAS and LOADM.

57 GW of peak load in 2025. Hiroaki (2008) built a regression model for Indonesia's peak load that considers electricity consumption by sector, electricity price, and GDP by sector as explanatory variables, finding 49 and 70 GW of peak load in 2028 in the base and high-growth cases, respectively. As mentioned in the introduction, the RUKN projects 189 GW of Indonesian peak demand in 2031 (MEMR (Ministry of Energy and Mineral Resources of the Republic of Indonesia), 2013). The RUKN applies a regression model, Simple-E, to forecast electricity demand based on historical data for power sales, installed capacity, number of customers, economic growth, and population as explanatory variables. It also uses the WASP (Wien Automatic System Planning) tool to simulate and optimize the power system. Zipperle (2014) models the Indonesian power system via URBS (Urban Research Toolbox: Energy System), a linear optimization model, and calculates the hourly electricity consumption by using aggregate sectoral load profiles. However, this study mostly focuses on the generation side and disregards efficiency improvements on the demand side. None of these studies considers end-use technologies and appliances, missing the potential impact on Indonesian peak load and installed capacity requirements due to diffusion of new and efficient technology alternatives.

Methods and assumptions

Our modeling builds on methods we have developed to forecast electricity demand and models impacts of energy-efficiency programs on energy demand and greenhouse gas emissions (e.g., McNeil, Letschert, Rue du Can, & Ke, 2013). We combine the activity and intensity elements of the Bottom-Up Energy Analysis System (BUENAS)—a stock accounting model projecting energy demand for appliances and equipment in the residential, commercial, and industrial sectors—with time-resolved daily profiles of equipment use via the new LOAD curve Model (LOADM). The resulting end-use hourly load profiles are then summed to yield a forecast of national electricity load curves for Indonesia, including the time of day and magnitude of peak system load.[4]

Modeling description

LOADM projects the peak demand and evolution of daily load curves at the national level from 2010 to 2030. Annual demand projections for end uses are provided by the bottom-up accounting framework, BUENAS. Fig. 1 shows the relationship between LOADM and BUENAS.

The BUENAS model forecasts the energy demand of common types of household appliances, lighting and heating and cooling equipment in both the residential sector and in non-residential buildings. The primary driver of energy use of these end uses are population, growing ownership rates of household appliances, increases in floor space in the commercial sector, and overall industrial economic growth. For major appliances where annual sales data are available, the total stock of appliances can be calculated from survival rates. When sales data are not available, ownership rates can be modeled through econometric diffusion equations (McNeil & Letschert, 2010). Once the total stock of equipment is determined, the electricity consumption or intensity of the appliance stock can be calculated according to estimates of the baseline intensity (annual energy consumption or efficiency) of the prevailing technology. Finally, stock and energy intensity are combined in order to calculate total final energy consumption as modeled by the flow of products into the stock and the efficiency of purchased units, either as new purchases or replacements of retired equipment. BUENAS models a high-efficiency or "policy" scenario by considering the impact of increased unit efficiency of new equipment relative to the baseline starting in a certain year. For example, if the average baseline unit energy consumption (UEC) of new refrigerators is 450 kWh/year, but a minimum efficiency performance standard (MEPS) takes effect in 2018 and requires a maximum UEC of 350 kWh/year, the stock UEC in the policy scenario will gradually become lower than that of the base case scenario due to the elimination of low-efficiency units under the standard. As all of the original stock are retired and replaces, the entire stock will generally be impacted by the standard. More details on the BUENAS methodology are given in McNeil et al. (2013).

LOADM uses appliance and sector-specific daily load profiles (i.e., for a 24-h period) obtained from the literature. LOADM can distinguish seasonal and day-of-week variants on daily load profiles. However, because the climate in Indonesia is tropical with abundant rainfall, high temperatures, and high humidity throughout the country, only one characteristic load profile is considered for each end use and sector in this analysis. In addition, we assume daily load profiles remain unchanged in the analysis period. The modeling of changes in individual demand profiles is difficult and beyond the scope of this paper.

Breakdown of demand and assumed load profiles

BUENAS for Indonesia covers demand for a range of electricity-consuming equipment:

- Residential sector—air conditioning, cooking (i.e., kettle, rice cooker), fans, lighting, refrigeration, standby, televisions (i.e., cathode ray tube [CRT], plasma, liquid crystal display [LCD], LED), laundry (i.e., clothes washer)
- Commercial sector—air conditioning, lighting, refrigeration
- Industrial sector—electric motors and distribution transformers, others

Fig. 2 and Fig. 3 show the normalized load profiles for different sectors and end uses in Indonesia. Standby power demand is assumed

[4] In this paper, the term "load curve" is used to mean the system load in each hour of an average day, and "load profile" is used to describe the hourly demand of individual sectors and end uses.

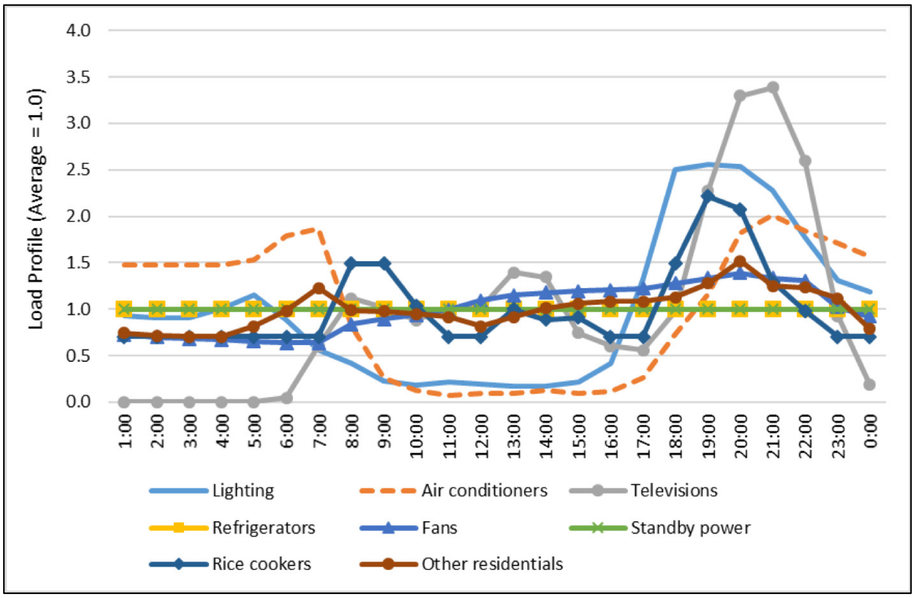

Fig. 2. End-use load profiles used in residential sector.

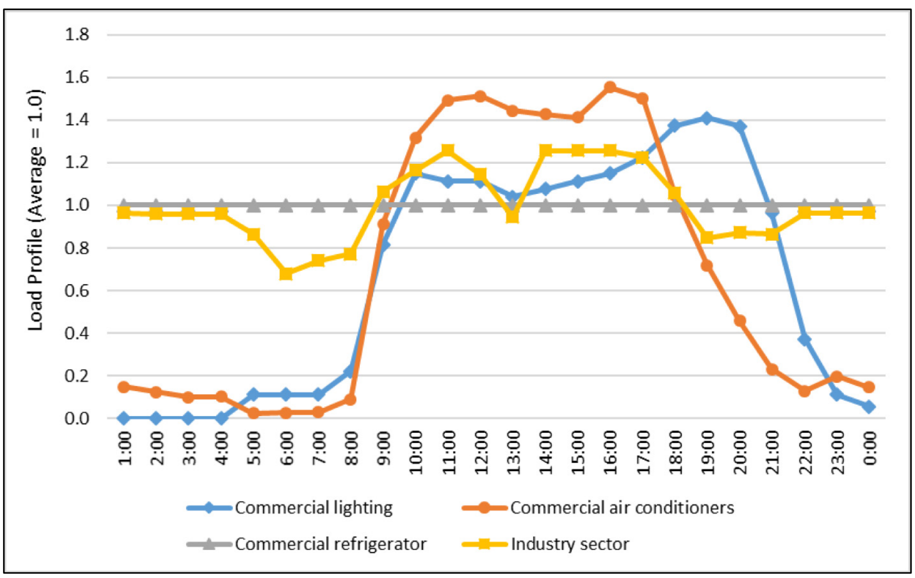

Fig. 3. End-use load profiles used in commercial and industrial sectors.

independent of geography, temperature, and time of day, so the load shape for this end use is assumed constant (flat distribution). Refrigerator power demand can vary vs. ambient temperature, but it is assumed relatively constant in the tropical environment. Sources of the load profiles are given in Table 1 and Table 2.

Table 1
Sources of residential load profile data.

End use	Source	Geographic region
Lighting	Tanoto, Santoso, and Hosea (2012)	Indonesia
Air conditioners	Garg, Maheshwari, and Upadhyay (2010)	Gujarat, India
Televisions	Garg et al. (2010)	Gujarat, India
Refrigerators	McNeil and Iyer (2009)	India
Fans	Kubota, Toe, Chyee, and Ahmad (2009)	Jahor Bahru, Malaysia
Rice cookers	Shimoda, Fujii, Morikawa, and Mizuno (2003)	Osaka City, Japan
Other residential*	Shimoda et al. (2003)	Osaka City, Japan
Standby power	EC (European Commission) (2007)	Europe

* Other residential includes kettles and clothes washers.

Fig. 4 shows an example of LOADM's ability to replicate historical load curves from 2011 for the Java-Bali system of Indonesia.[5] Our final load curve accounts for transmission and distribution losses, which totaled 9.77% in 2015 (MEMR (Ministry of Energy and Mineral Resources of the Republic of Indonesia), 2016). Discrepancies between actual and modeled load for 2011 can be traced to various factors. We would not expect exact agreement, because there are undoubtedly some end uses, such as small plug loads and industrial equipment, not captured by the model. In addition, even though we customized the appliance load profiles that we use for Indonesia based on a residential survey performed by MEMR in 2015 (MEMR (Ministry of Energy and Mineral Resources of the Republic of Indonesia), 2015b), there may

[5] The Java-Bali system represented 74% of Indonesia's total peak load in 2011.

Table 2
Sources of commercial and industrial load profile data.

End use	Sector	Source	Geographic region
Lighting	Commercial	Garg et al. (2010)	Gujarat, India
Air conditioners	Commercial	Garg et al. (2010)	Gujarat, India
Refrigerators	Commercial	Garg et al. (2010)	Gujarat, India
Industry sector	Industrial	IEOS (Indonesia Energy Outlook and Statistics) (2006)	Indonesia

still be some discrepancies. Also, in the absence of data for Indonesia, commercial-sector load profiles are based on data for India. In spite of these sources of uncertainty, the correlation between the actual and modeled load curves is 0.93.

Fig. 5 compares the modeled peak load with historical data. The margin of error stays within the range of −1.5% to +4%. Although the discrepancies between modeled peak loads and actual peaks are small, we caution against interpreting this agreement as an indication of very high precision owing to the reasons mentioned above.

General considerations

Macroeconomic assumptions

The population of Indonesia in 2015 was 255.5 million, making it the world's fourth most populous country. About half of the population (46%) still lives in rural areas (World Bank, 2016a). The United Nations (UN) predicts that 68% of the population will be urbanized by 2025 (World Bank, 2016b). It is assumed that the population in Indonesia will increase over time with an average annual growth rate of 1% to reach 296 million by 2030 in line with Indonesian government projections (BPS (Badan Pusat Statistics), 2013) and UN forecasts (UNFPA (United Nations Population Fund), 2014). Fig. 6 shows the elasticity between electricity consumption and GDP in Indonesia between 2000 and 2013. Historical electricity consumption has been strongly linked with GDP, with an implied elasticity of about 1.2. BUENAS uses economic growth along with other key drivers—such as population, urbanization rate, and electrification rate—to model Indonesia's electricity demand. After 2010, the GDP per capita is assumed to increase at a rate of 3.9% per year, reaching US$8837 (2007 dollars) in 2030. Table 3 provides the household size and electrification rates assumed in this study. Household size declines 0.8% per year, and electrification rate increases 1.8% per year to reach 100% in 2030. Commercial end uses energy

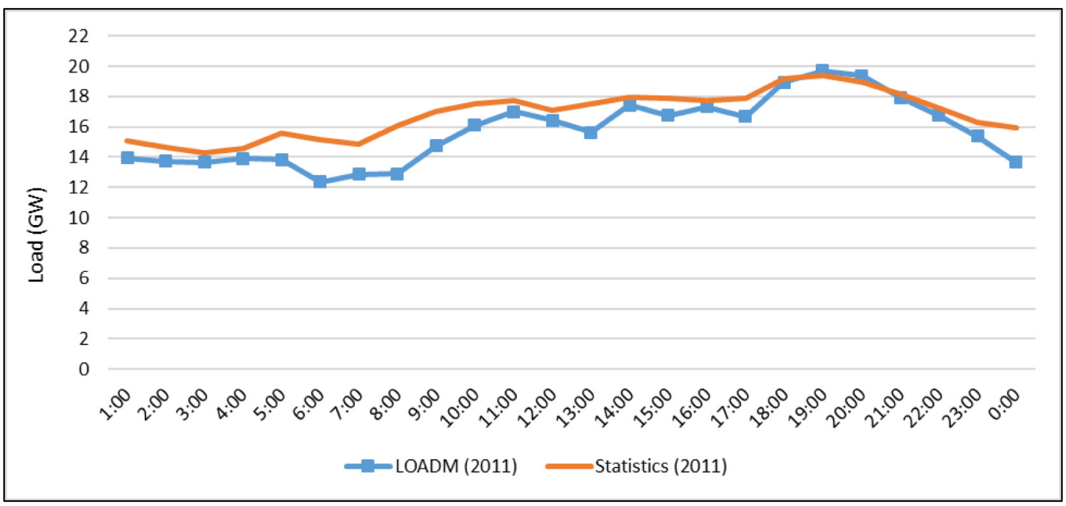

Fig. 4. Comparison of typical daily load curve of Java-Bali system in 2011, modeled with LOADM vs. actual statistics (Batih & Sorapipatana, 2016).

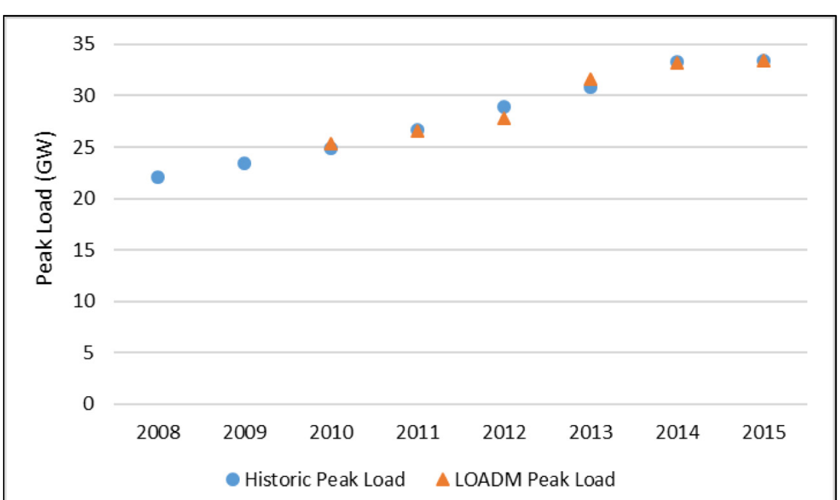

Fig. 5. Comparison of peak load estimates for Indonesia from 2008 to 2015, modeled with LOADM vs. historical data (MEMR, 2016).

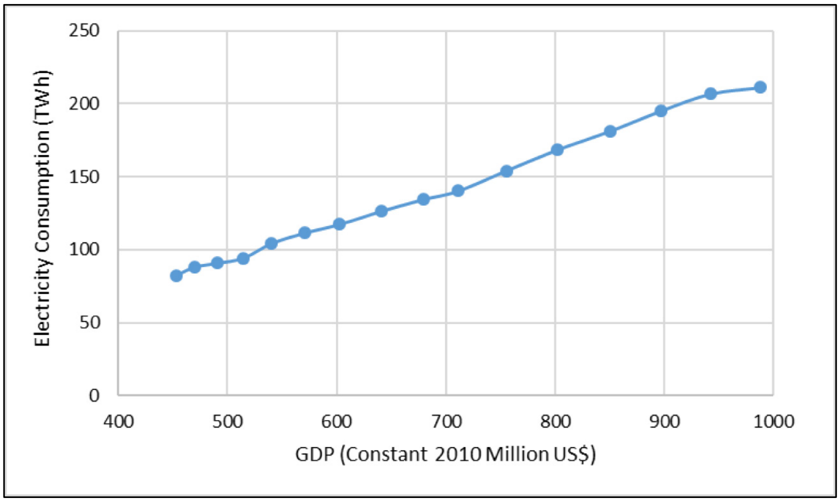

Fig. 6. Electricity consumption relation to GDP between 2000 and 2015 (MEMR, 2016).

consumption are projected according to expected growth in commercial building floor space (in m^2), which is in turn driven by GDP per capita in an econometric model described in (McNeil et al., 2013).

Stock and adoption modeling

Energy savings from energy efficiency programs generally rely on diffusion of new high-efficiency equipment into the stock. Therefore, historical sales data and forecasts of sales in the future (Euromonitor International, 2013; BSRIA (Building Services Research and Information Association), 2014) present a relatively accurate, though still somewhat uncertain picture of potential impacts of policy. When available, these data are combined with distributions of useful life of appliances in a stock turnover analysis, yielding total number of appliances in each year, as well as the distribution of age of stock (sometimes called 'vintage'). Adoption (ownership) levels for these years are then calculated by dividing the stock by the number of households in the country. In the absence of sales data, BUENAS models diffusion and stock of residential equipment directly to 2030 according to macroeconomic parameters such as GDP, electrification, urbanization, climate parameters, and population as drivers. BUENAS models end use electricity consumption in the commercial sector as energy intensity (kWh/m^2) which grows with economic development in terms of GDP per capita. Each of the three commercial end uses studied (lighting, refrigeration, and air conditioning) evolve according to distinct econometric parameters determined by historical data across countries.

Adoption levels of major household appliance remain low in Indonesia in the base year of 2010, with ceiling fans and televisions being notable exceptions. For example, only 31% of households were reported to own a refrigerator in that year, and more expensive goods such as air conditioners were owned by a very small portion of the country (adoption rate of 8% in 2010). While the television market is moving rapidly to LCD and light-emitting diode (LED) flat-screen televisions, most households still own CRT televisions, which is the most inefficient television group in the market. The current low rates of appliance ownership (i.e., adoption) coupled with high economic growth rates therefore imply that the residential sector in Indonesia is poised for rapid growth in electricity demand, which will in turn drive overall electricity demand in the country in the coming decades. Fig. 7 shows significant growth in modeled ownership rates in the residential-sector, especially for large appliances like refrigerators and air conditioners (Fig. 7). These projections agree with those in APERC (Asia Pacific Energy Research Centre) (2011).

Table 3
Macroeconomic assumptions used in the BUENAS model.

	2010	2030	Annual growth
Population (million)	241	296	1.0%
GDP (billion $2007)	991	2619	5.0%
GDP per capita ($2007)	4118	8837	3.9%
Household size	3.90	3.32	−0.8%
Electrification rate	70%	100%	1.8%
Urbanization rate	54%	69%	1.3%
Industrial GDP Fraction	47%	46%	−0.1%

Population growth based on BPS (Badan Pusat Statistics) (2013) and UNFPA (United Nations Population Fund) (2014). Remaining assumptions based on World Bank (2016c) indicators and forecasts developed using historical trends.

Annual unit energy consumption

We evaluate a BAU scenario that assumes static efficiency with the exception of lighting (incandescent lighting is progressively phased out by 2030) as well as a best available technology (BAT) scenario. The BAT scenario reflects the technical potential for energy efficiency afforded by the best technologies currently available on the global market or designed from high-efficiency components. We use BAT assumptions for residential-sector end uses such as lighting, air conditioners, and refrigerators (Letschert et al., 2013). This potential is evaluated assuming that technologies would become mandatory for new products being sold in the Indonesian market by 2018. The BAT scenario is aspirational by design, with the primary goal of identifying energy efficiency's potential in Indonesia. While significant improvement is also possible for other residential-sector end uses, and for end uses in the commercial and industrial sector, these are omitted due to lack of data.

Fig. 8 shows the projected contribution of different lighting technologies used by households in Indonesia between 2010 and 2030 under the BAT scenario. Unlike data for other appliances, sales data for lighting are not available. Therefore, adoption rate projections for this end use are modeled econometrically (McNeil & Letschert, 2010). Market shares are derived separately and combined with stock in Fig. 8. The share of linear fluorescent lamps remains constant between 2010 and 2030; improvements in efficiency are due to improvements in ballast technology. Within the remaining lighting market, incandescent lamps are phased out by 2017 and replaced by compact fluorescent lamps (CFLs) and LEDs (MEMR (Ministry of Energy and Mineral Resources of the Republic of Indonesia), 2015a). In the BAU scenario, all shares remain constant after 2015. In the BAT scenario, LEDs replace CFLs by 2022.

Unit energy consumption is the annual electricity consumption of a single appliance, sold in the year of forecast. It is generally a function of

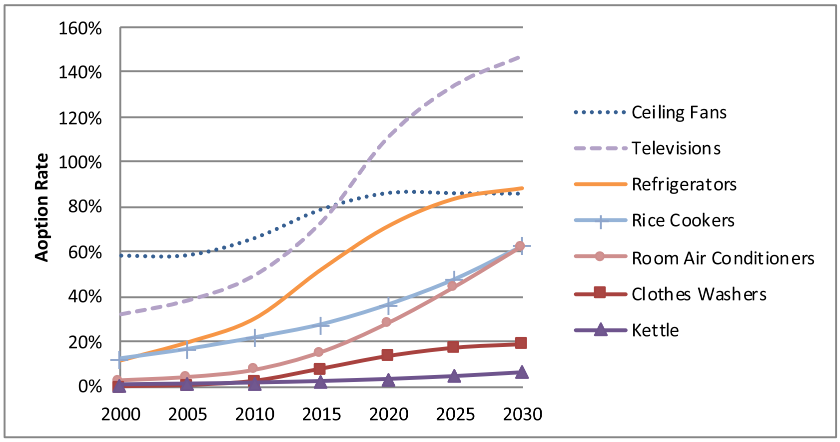

Fig. 7. Projected adoption of residential appliances (2000–2030) from BUENAS.

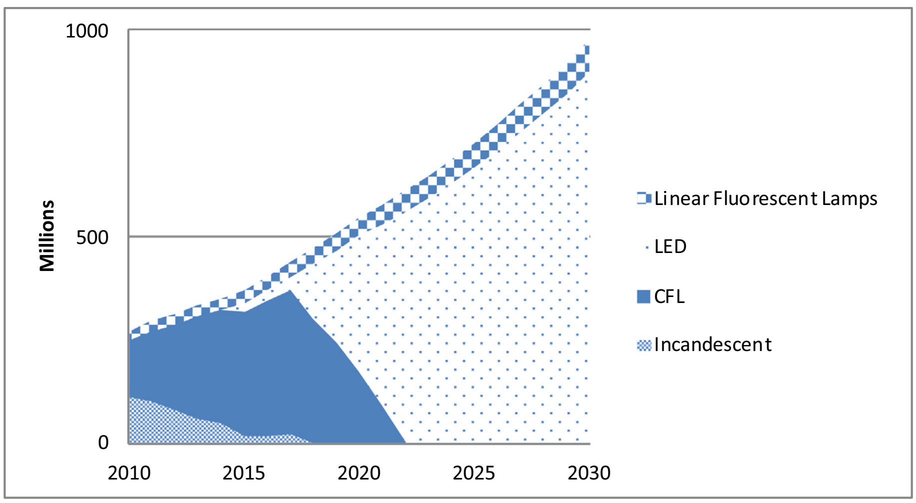

Fig. 8. Projected lighting stock by technology in the residential sector (BAT assumptions). CFL = compact fluorescent lamp, LED = light-emitting diode.

the appliance capacity (size, wattage, etc.), hours of use, and efficiency. We derive UEC from various sources (Table 4).

Results

Load curves under the BAU scenario

Projection of Indonesia's daily load curve into the future is based on annual electricity demand projections from the BUENAS model. As shown in Fig. 9, the BAU scenario BUENAS projection is much lower than the MEMR projections (e.g., 22% lower in 2020 and 51% lower in 2030) and the State Electricity Company (PLN) projection (15% lower in 2020). The differences are due to different calculation methods and assumptions considered in the analysis. MEMR and PLN use top-down approaches driven mainly by population, electricity access, and GDP growth, whereas BUENAS applies a bottom-up approach, carefully modeling future market adoption of all end uses included in the analysis (McNeil & Letschert, 2010). In addition, population and GDP growths considered in our projections (4.8% GDP growth and 1% population growth per year) are moderate compared with MEMR assumptions (e.g., 8% GDP growth and 1.7% population growth per year). Fig. 9 also shows a simple scaling down of the MEMR projections, applying an annual GDP rate of 4.8%, which results in MEMR projections much closer to our modeled projections (only 4% higher in 2020 and 29% higher in 2030). Furthermore, some end uses, such as electric irons, are not included in our projections.

Fig. 10 shows the evolution of hourly load curves for Indonesia between 2010 and 2030 in the BAU scenario. Indonesia's average peak demand is projected to increase by 73% (reaching 43.7 GW) in 2020, by 142% (reaching 61.2 GW) in 2025, and by 205% (reaching 77.3 GW) in 2030, compared with 25.3 GW in 2010. Meeting this demand growth would require adding electricity generation capacity of 18.4, 35.9 and 52 GW in 2020, 2025 and 2030, respectively. Residential electricity consumption, particularly for lighting, is the main contributor to the evening peak in 2010. Almost 26% of electricity at peak demand

Table 4
unit energy consumption in BAU and BAT scenarios (kWh/year).

	BAU UEC	BAT UEC	% Reduction	Source
Air conditioners	1661	729	56%	(Letschert et al., 2017, Shah, Phadke, & Waide, 2013)
Refrigerators	454	186	59%	(Shah et al., 2013)
Televisions (LCD)	58	26	55%	(Park, Phadke, Shah, & Letschert, 2013)
Fans	150	66	56%	(Shah, Sathaye, Phadke, & Letschert, 2015)
Standby power	18	4	78%	(Letschert et al., 2013)
Linear fluorescent lamp	67	60	11%	(Letschert et al., 2013)

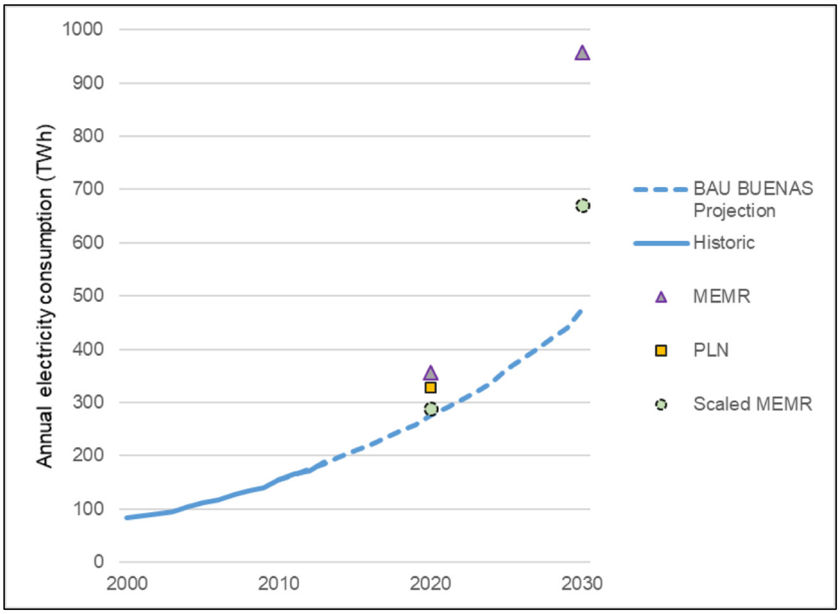

Fig. 9. Annual electricity consumption in Indonesia (historical data 2000–2013, projections 2010–2030).

is used by lighting. In addition, television, which accounts for 18% of the peak demand, and residential lighting together have more electricity demand in the peak hour than do the commercial and industrial sectors combined (which account for 35% of the peak demand), in 2010.

Fig. 11 compares modeled projections with a load curve scaled-up by an average annual growth rate of 6.9%, which is the average historical growth of the peak load between 2008 and 2013. Simple rescaling yields deviations with a difference of 19 GW in 2030 when compared with LOADM projections for 2030. Fig. 11 also shows the average peak load forecast of MEMR for 2030, which is 2.2 times higher than our projection. This discrepancy can be explained by different assumptions and modeling approaches as mentioned before. While MEMR's point forecast for peak load is mainly driven by econometric and demographic factors, we model energy demand by end use and apply individual technology load profiles to generate the overall load curve. Energy demand by end use is a product of market adoption of end uses, housing stock, GDP, and commercial floor space. When the MEMR projection is adjusted using a simple scale-down according to a GDP growth rate of 4.8%, the gap between peak load projections narrows, but the scaled MEMR projection still stays 1.5 times higher than our result.

The drivers behind our load curve evolution are identified in Fig. 12, which shows how changes in individual technology profiles combine under the BAU scenario in 2030. In 2030, the electricity demand at the peak is mostly distributed among residential air conditioners (21 GW), the commercial and industrial sectors (13.3 GW and 14.8 GW), and residential lighting, refrigerators, and televisions (13 GW, 4.5 GW, and 3.5 GW, respectively). The share from residential air conditioners, lighting, and refrigerators (50%) is larger than the share from the commercial and industrial sectors (36%) at the peak in 2030. The contribution of air conditioners to peak load grows roughly 10-fold between 2010 and 2030, whereas the share of lighting at peak decreases from 26% in 2010 to 17% in 2030 owing to the phase-out of incandescent lights. In addition, the load curve becomes slightly less peaky in 2030, with the peak to average load ratio decreasing to 1.43 in 2030 from 1.54 in 2010.

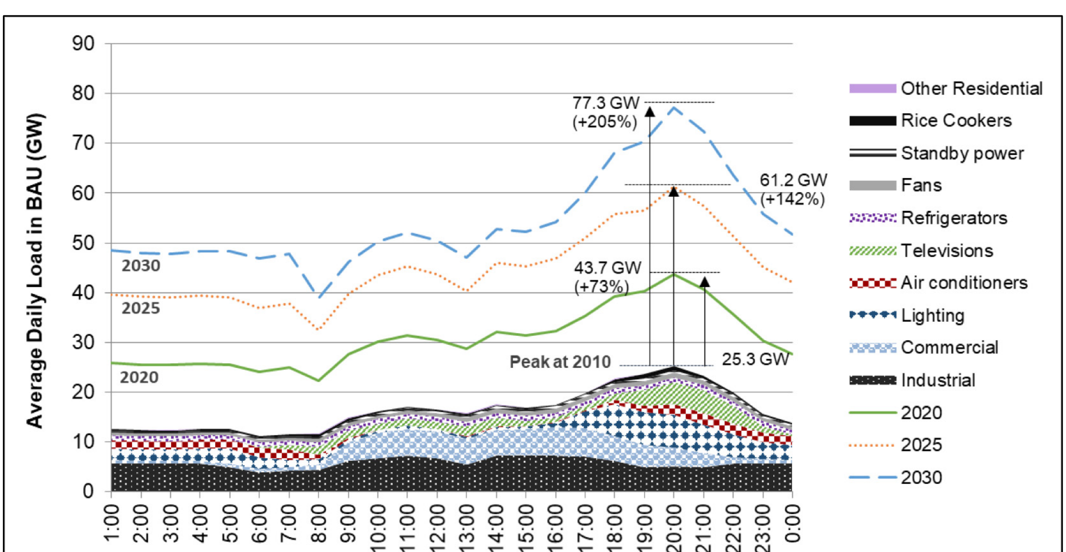

Fig. 10. Evolution of Indonesian daily load curve in the BAU scenario between 2010 and 2030; shaded areas represent modeled end-use load profiles in 2010.

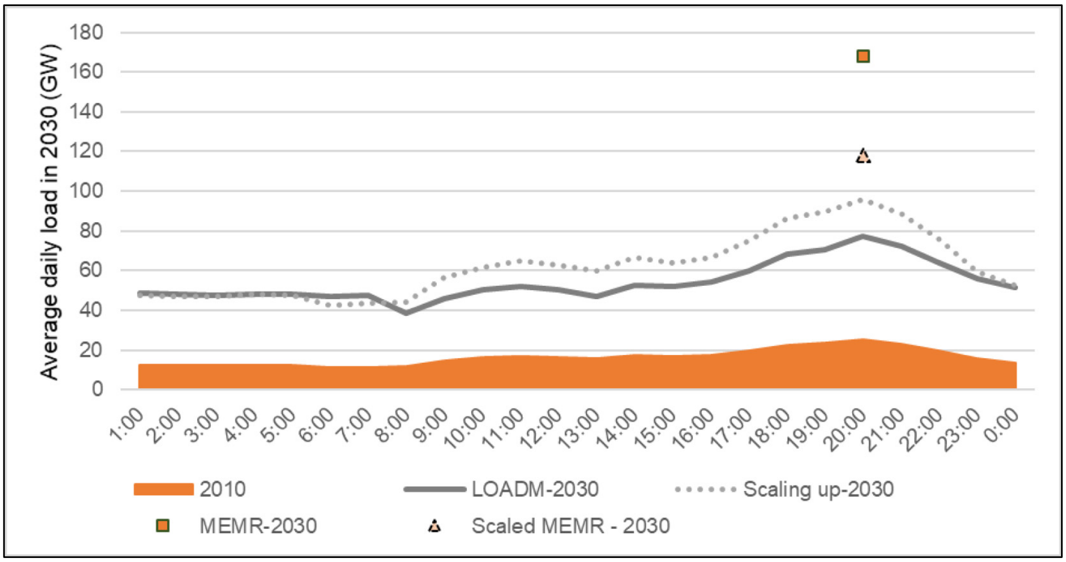

Fig. 11. Comparison of average daily load curve projected by LOADM for 2030 (BAU scenario) with scaled-up historical load profile and MEMR peak load forecast.

Load reductions under the BAT scenario

In the BAU scenario, peak load growth is strongly influenced by the growth of appliance adoption (ownership) in Indonesian households. Fig. 13 compares the daily load curves in the BAU scenario in 2025 and 2030 with the corresponding curves in the BAT scenario. Because of the introduction (in 2018) and subsequent adoption of energy-efficient lighting, appliances, and equipment, peak load increases more slowly in the BAT scenario. The system peak load is projected to be 15.2 GW lower in the BAT scenario in 2025 and 22.9 GW lower in 2030, corresponding to roughly 36 and 54 fewer large power plants needed in 2025 and 2030. Summing average load savings over the year yields total electricity savings in the BAT, which we find to be 69.8 TWh in 2025 and 106.9 TWh in 2030. Application of the current grid emission factor of 0.79 kg CO_2/kWh yields mitigation of 55.2 million metric tons (Mt) CO_2 (25%) in 2025 and 84.5 Mt CO_2 (30%) in 2030. These results show that nearly 27% of the CO_2 emission reduction of the energy sector target in 2030 could be achieved via efficient appliances and lighting (84.5 Mt CO_2 compared to 314 Mt CO_2).

Fig. 14 and Fig. 15 show the details of the power savings in the BAT scenario compared with the BAU scenario in 2025 and 2030. Energy-efficient residential air conditioners are the largest contributor to peak load reduction under the BAT scenario, resulting in reductions of 7.3 GW in 2025 and 11.8 GW in 2030 (Table 5).

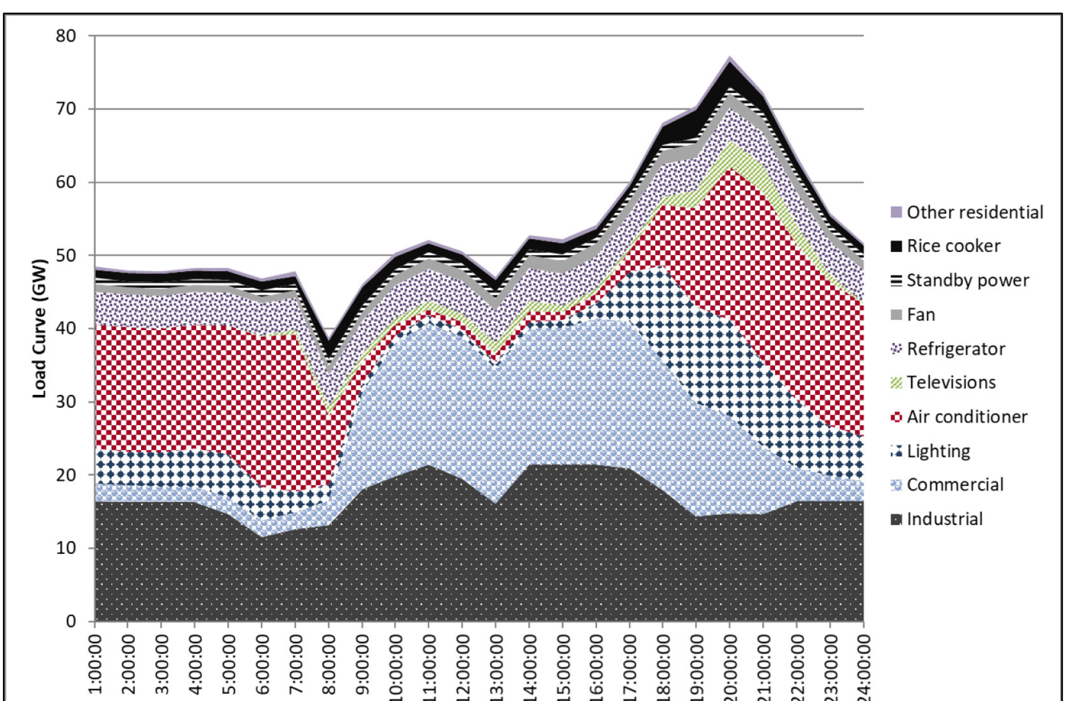

Fig. 12. Indonesia average daily load curve in the BAU scenario in 2030 by end use and sector.

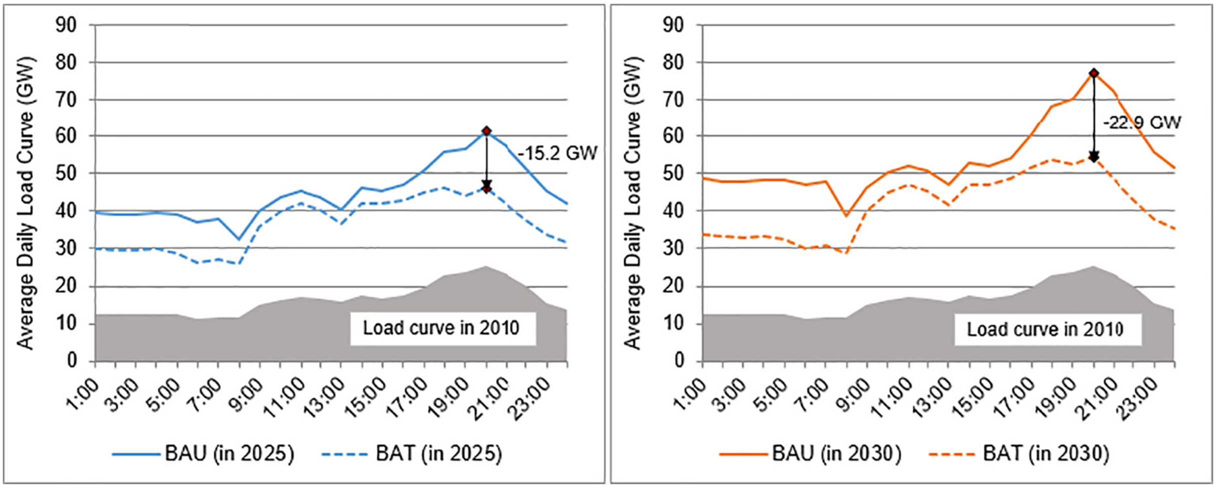

Fig. 13. Indonesia average daily load curves in the BAU and BAT scenarios in 2025 and 2030.

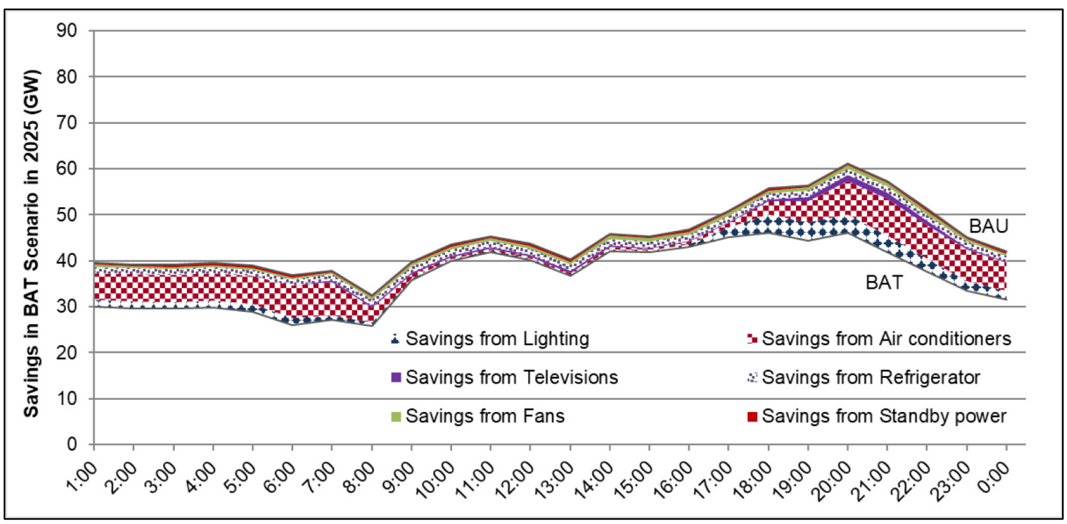

Fig. 14. Average daily power savings in the BAT scenario in 2025, compared with the BAU scenario.

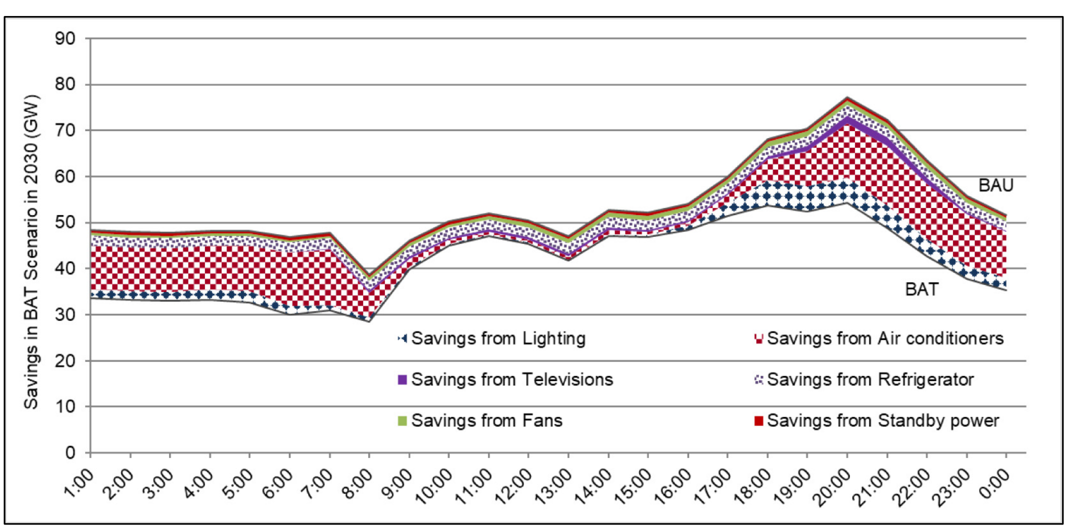

Fig. 15. Average daily power savings in the BAT scenario in 2030, compared with the BAU scenario.

Table 5
Contribution of sectors and end uses to reduced peak demand in 2025 and 2030 in the BAT scenario compared with the BAU scenario.

	Reduction in 2025		Reduction in 2030	
	(GW)	(%)	(GW)	(%)
Lighting	4.0	6.6%	5.5	7.1%
Refrigerator	1.3	2.2%	2.1	2.8%
Air conditioner	7.3	11.9%	11.8	15.3%
Fans	0.8	1.3%	1.1	1.4%
Televisions	1.2	2.0%	1.7	2.2%
Standby power	0.5	0.8%	0.7	0.9%
Total	15.2	24.8%	22.9	29.6%

Discussion and conclusions

Several major conclusions emerge from our analysis of Indonesian electricity load projections. We show that peak load, and therefore generation capacity needs, could grow 205% (52 GW) between 2010 and 2030 in our BAU scenario, to a total of 77.3 GW; this result broadly agrees with the RUPTL estimate of Indonesia's future capacity requirements. A few residential end uses—led by air conditioners, lighting, refrigerators, and televisions—account for over half of national peak demand in 2030, with the remaining demand attributed to the commercial and industrial sectors. The concentration of demand in a few end uses enables meaningful estimation of demand avoidance due to efficiency measures in our BAT scenario, which we estimate to be 26.5 GW, or 34.3%, compared with the BAU scenario in 2030. Over half of these savings could come from residential air conditioners alone, which suggests that well-understood programs such as MEPS could avoid tens of billions of dollars of capital costs over the next decade and a half.

Although we believe these results to be robust compared with less detailed estimates, caution is warranted for the following reasons:

- *Lack of end-use detail* – The modeling neglects some smaller end uses and treats the commercial building and industrial sectors in the aggregate. The relatively close correlation between the resulting load shapes shown in Fig. 4 suggests the level of error caused by this, which we estimate at a few percent.
- *Use of proxy data* – End-use load profiles were not widely available for Indonesia, so we relied on data from other countries. We believe that most of these profiles are relatively similar for the countries where data were available. Again, the error caused by this approximation is suggested by the difference in modeled vs. actual load curves. The importance of some end uses—specifically residential air conditioners—does point to the need for improved data collection in this area, however.
- *Policy dependence* – Our approach uses MEPS as a model of energy-efficiency policies. Savings in 2025 are significantly lower than in 2030 because of the relatively slow diffusion rate of this policy, which affects new equipment only. MEPS are modeled because of their relatively strong and predictable savings outcomes; other policies are available to decrease end-use loads and improve efficiency, however, and could have similar impacts.

Finally, any such projection of aggregate energy demand is highly dependent on assumptions made about the increased adoption of certain types of equipment. Because of the overwhelming importance of residential air conditioning, we performed a sensitivity analysis on the adoption of this appliance.

Fig. 16 compares the Indonesian daily load curve in 2030 under the BAU scenario with two alternative air conditioner adoption scenarios. Air conditioners have an adoption rate of 73.4% in 2030 under the BAU scenario. A 25% higher adoption rate (from 73.4% to 92%) increases the peak load by 10% (from 77 to 85 GW). A 25% lower adoption rate (from 73.4% to 55%) decreases the peak load 12% (from 77 to 68 GW).

Fig. 17 compares the Indonesian daily load curve in 2030 under the BAU scenario with the load curve under a scenario that assumes a much broader load profile for air conditioners, including a constant maximum load between 7 pm and 7 am. The broader air conditioner load profile results in a smaller evening load peak and a smoother load curve.

In conclusion, our analysis represents a first look at integrating bottom-up end-use electricity demand forecasting and scenario building with detailed end-use demand profiles to predict future system load curves and evaluate the potential for energy efficiency to mitigate peak demand growth. Although some aspects of this analysis are not unique, we believe combining detailed end-use data with nationwide

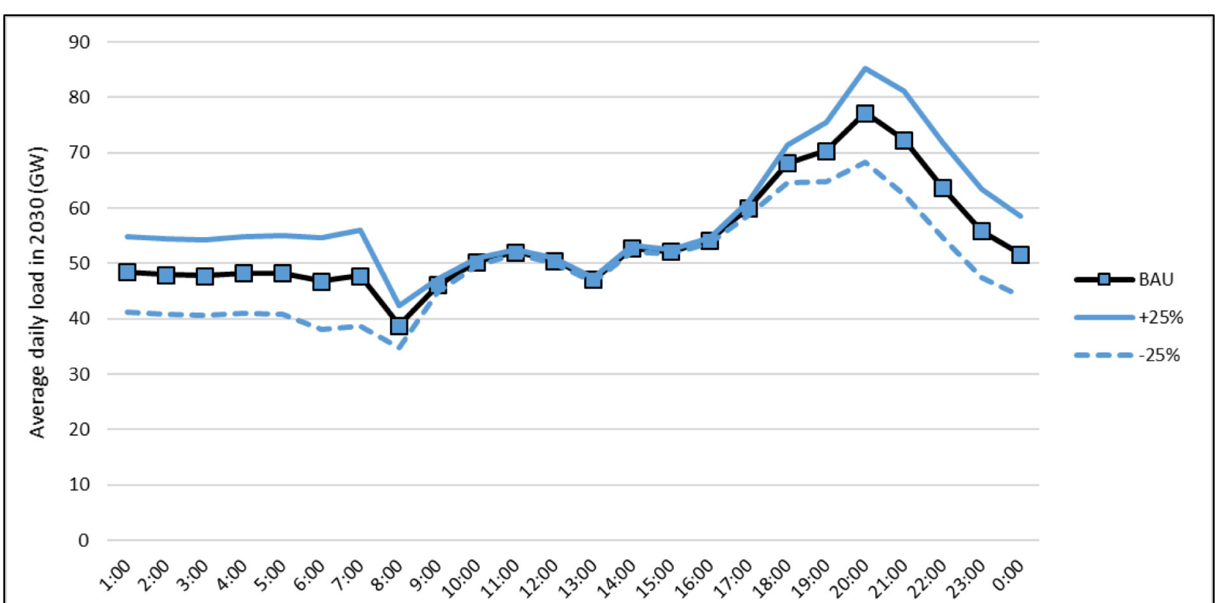

Fig. 16. Daily load curves in 2030 under the BAU scenario and different air conditioner adoption scenarios (±25% scenarios represent air conditioner adoption rates of ±25% compared with the BAU scenario's adoption rate).

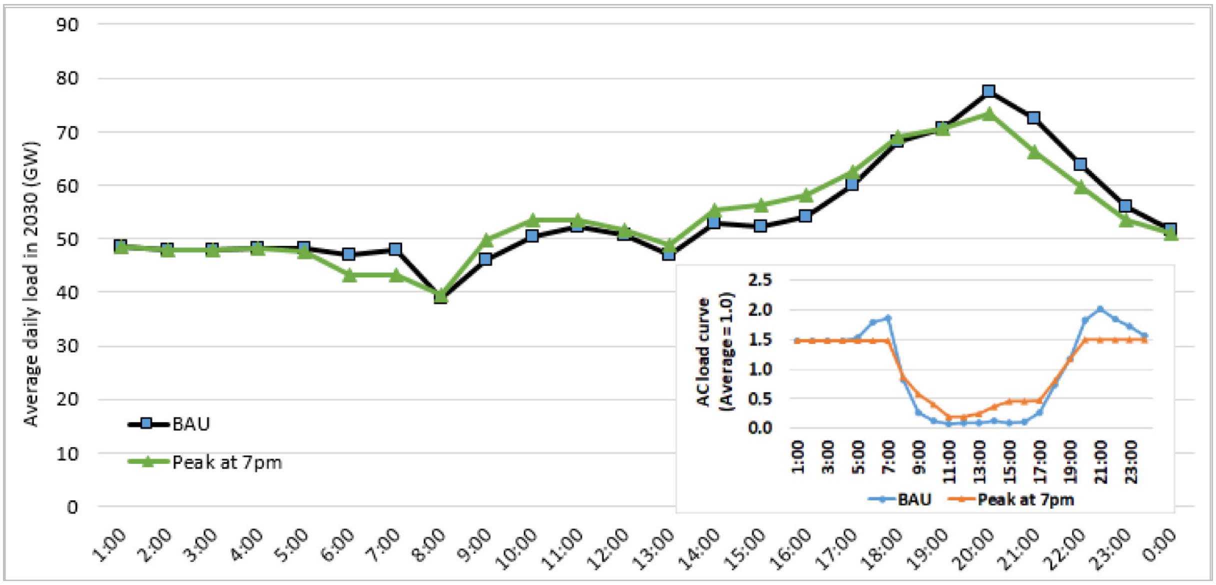

Fig. 17. Daily load curves under different air conditioning load profiles.

system load curve projections in a developing country is novel. We have refined this analysis over the past few years in direct collaboration with the Government of Indonesia, and we believe significant progress has been made in communicating the potential impact of energy efficiency to high-level Indonesian policymakers. Discussions of a national roadmap to achieve the identified energy and climate benefits are ongoing with our counterparts.

Although significant uncertainties are present in any modeling and forecasting exercise, our analysis is intended to achieve sufficient accuracy to contribute meaningful insights about future peak loads and the impacts of energy-efficiency policies on generation capacity. These impacts may be a higher priority to local policymakers than energy savings alone, owing to the high costs of either building new power plants or facing damaging power shortages. Indonesia is currently facing these issues, with an estimated $150 billion potentially at stake in terms of new power plant capital costs and associated transmission and distribution infrastructure. Indonesia is important because of its rapid economic growth and tropical climate, but it is not unique—we hope the methods described here can be applied to other emerging economies as well.

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