Association of Energy Engineers

Volume 8
Issue 3 | 2026

Alternative Energy & Distributed Generation Journal

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ISSN: 2643-6973 (Print)
ISSN: 2643-6981 (Online)

Alternative Energy and Distributed Generation Journal

Stephen A. Roosa, Ph.D., CEM, Editor-in-Chief
Vol. 8, No. 3—2026

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JOURNAL OF THE ASSOCIATION OF ENERGY ENGINEERS®

ISSN: 2643-6973 (print)
ISSN: 2643-6981 (on-line)

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Alternative Energy and Distributed Generation Journal (ISSN 2643-6981) is published quarterly by the Association of Energy Engineers, 3168 Mercer University Drive, Atlanta, GA 30341. Production Office: 3168 Mercer University Drive, Atlanta, Ga. 30341, 770-447-5083, ext. 224.

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Editor's Desk

The Variable Output of Solar PV Arrays

Optimizing the potential electrical generation from the installation of a solar photovoltaic (PV) system for a commercial or industrial site can be challenging. The production of electricity from a solar PV array varies due to factors such as the site location, weather conditions, and orientation. Energy engineers are often tasked with developing an estimate of solar PV system output without having physically visited the potential development site—certainly a challenging assignment. To confound the engineer, there are innumerable potential configurations. Solar PV arrays are location sensitive and vary in the types of modules, orientation, racking systems and load requirements. Arrays can be located on open land, floated on ponds or lakes, mounted on rooftops, used as awnings to provide shade, or installed on canopies. Canopy structures are often used in existing automobile parking areas and customized to supply power for electric vehicle charging stations.

Information that the designer requires would include the site location, physical site layout, electrical utility locations, and locations of nearby buildings and structures. Ultimately an estimate of the solar potential of a preliminary solar PV configuration will be needed for proof-of-concept. If the engineer is unable to physically visit the development site, basic data may need to be accumulated virtually. Virtual analysis will often use a software platform such as Google Earth to gather information about the site. Preliminary analysis of the generation potential might use an on-line software program such as PVWatts, developed by the National Renewable Energy Laboratory (NREL) to estimate the electrical generation potential of a solar array [1].

Solar Power Is Intermittent

The solar constant is the average density of solar radiation measured outside Earth's atmosphere and at Earth's mean distance from the sun; it is 1.360 kW/m^2 or 0.13 kW/ft^2. The amount of solar insolation that

penetrates the atmosphere and reaches the surface of a solar collector is less; it varies widely based on non-controllable conditions such as season, time-of-day, cloud cover, air pollution, ambient conditions, etc. The length of time each day that the sunlight is available varies. Substantially more daylight is available during the summer months than in winter months in non-tropical regions. In winter months, snow and ice might accumulate on the surface of the collectors which reduces module efficiency until it is removed either by natural conditions or physical intervention. Overheating can reduce panel efficiencies. Because the electricity comes from the flow of electrons inside an electrical circuit, heat waves cause the electrons to vibrate too actively which reduces voltage. Nearby trees may need to be trimmed to prevent an array from being shaded. Development in urban areas may lead to high-rise construction on a site adjacent to a solar array causing it to be shaded during parts of the day which reduces the amount of power generated. These are reasons why solar power is an intermittent renewable resource.

Maintenance is required to optimize the output of a solar array. Controllable conditions that effect the output of solar collectors include repairing or replacing damaged panels and removing debris from the collector surface. Effective strategies include performing physical assessments, remote monitoring, and performing routine maintenance. Infrared thermography can be used to help identify damaged solar PV modules. The impacts of intermittent generation can be resolved or lessened when utility interconnections and energy storage systems are utilized.

Solar Module Efficiencies

While solar power can be used to generate electricity using thermal energy, solar PV cells directly convert sunlight to electricity. Electrical generation potential is greatest when the sun is shining. A key parameter used for estimating solar array output is system efficiency. Silicon solar cells use natural daylight in the red to violet spectrum (near the infrared range) with wavelengths of 400-700 nm for electrical generation. This is the spectrum of light visible to the human eye. The ability of solar cells to convert this available energy into electricity varies.

Solar cell efficiency is typically defined as the percentage of the solar energy falling on the cell's surface that is converted into electrical energy.

Module (panel) efficiency is the overall efficiency of the combination of photovoltaic cells assembled into a module. The true efficiency measure of a solar PV module is its "energy yield" as determined by laboratory testing. Energy yield is the actual output in kilowatt hours (kWh) as measured by recording equipment over time and verified by independent test facilities.

Common categories of solar PV modules include silicon and thin film photovoltaics. Silicon PV modules are one of the most prevalent commercial technologies and are classified as either monocrystalline silicon (c-Si) or polycrystalline silicon (mc-Si). Monocrystalline silicon photovoltaic cells are typically made using the Czochralski process in which single-wafer silicon cells are cut from cylindrical ingots of highest-grade refined silicon; they have higher efficiencies, longer life, provide better low light and low temperature performance, and are more costly. Polycrystalline silicon cells are made from raw silicon that is melted and poured into a square mold; when cooled they can be cut into perfectly square wafers consisting of many small crystals. Modules that use polycrystalline silicone cells are less efficient than monocrystalline panels, but are less affected by high temperatures, have better high-temperature performance, and are less costly. Cell efficiencies for monocrystalline cells are a maximum of 26.8%; for multi-crystalline cells the maximum is 23.3%. Thin-film PV modules are the least efficient but can be applied to different types of surfaces (e.g., vinyl, glass, or stainless steel). All solar PV cell technologies natively produce electricity in the form direct current (DC). Inverters are needed to transform DC power to AC.

Solar PV cells operate at their peak efficiencies at temperatures of 25°C (77°F). When higher temperatures are experienced, the panel's temperature increases, leading to increased resistance within the PV cells [2]. The resistance increases the amount of heat generated, leading to a further reduction in efficiency [2]. The decline in performance becomes more evident in places with hot climates where temperatures repeatedly exceed 40°C (104°F). Research has shown that most solar panels that use silicone technologies exhibit a relatively linear rate of decline in output over time [3]. They have a median degradation rate of about 0.5% per year with the mean in the range of 0.8-0.9% per year; the rate could be higher in hotter climates and mounting configurations that

lead to sustained higher temperatures (i.e., roof-mounted systems) [3]. A degradation rate of 0.5% implies that production from a solar panel will decrease at an uncompounded rate of 0.5% per year. This means that in year 20, the module is producing approximately 90% of the electricity it produced in the year it was initially installed. Degradation rates tend to be higher for multi-crystalline silicon solar PV modules than for monocrystalline silicon solar PV modules.

Solar cells are assembled groups of panels or modules. When configured into panels, the module efficiency is less than cell efficiencies. NREL provides module efficiencies for various types of solar PV panels that have been standardized and confirmed by independent, recognized test labs [4]. Efficiencies typically range from 20.4% to 26.2% for commercial silicone-based solar PV modules. However, hybrid panels that use the heat produced for process applications can achieve efficiencies up to 40% [4].

The amount of electricity generated by a solar array varies based on the number and type of solar modules used, their efficiencies, panel age, physical orientation, and mounting systems. For solar photovoltaic arrays, module efficiency equates to space and labor efficiency; higher module efficiency means that less collector surface area and installation labor is required to generate the amount of electricity needed. Output also varies based on the type and orientation of the selected mounting system. Typical types of mounting systems for solar arrays include field, roof, or canopy fixed tilt systems, and single-axis tracking. Dual-axis tracking systems are an available but rarely used option.

Causes of Variable Solar Array Electrical Output

One of the problems we find in practice is that the actual electrical generation of installed solar arrays often falls short of design expectations. What causes these shortfalls in electrical production? Fluctuations in the amount of light incident on the panel, such as at dawn and dusk, cloud cover, passing storms, and debris are often cited. Lack of maintenance, such as allowing dust, leaves, snow, or ice to accumulate on the panels can cause solar arrays to underperform [5]. While weather conditions are often cited as the uncontrollable and principal cause, other factors, often occurring in combination, are usually the culprit [5]. The output of solar arrays is variable. Overestimating system output can be a result of:

- Using cell efficiencies rather than tested module or panel efficiencies.
- Failure to account for module degradation.
- Excluding system losses (e.g., from inverters, converters, etc.).
- Unaccounted losses in turn-around cycles from battery energy storage systems.
- Accepting the rated DC output in kWh as usable AC power.
- Panel overheating (often caused by not elevating the panels above mounting surface).
- Maintenance issues such as cleaning or snow removal.
- Unidentified damage to the solar PV modules.

It is important to consider the interrelationships among the system components and how system efficiencies may be impacted. Using a conservative system derating factor is one way to help ensure that the electrical generation of the system is not overestimated given the widely-variable design uncertainties. If estimating output over number of years, a degradation rate needs to be included in the analysis.

Considerations for Practitioners

There are many ways to incorporate solar energy systems in existing commercial buildings. The amount of electricity generated by a solar array varies based on the number and type of solar modules used, their efficiencies, panel age, physical orientation, maintenance, and mounting systems [5]. For the practitioner, it is important to consider the interrelationships among the components of a solar PV system and how system efficiencies may be impacted.

Installing solar arrays on roofs, in open fields, and on specially designed canopy structures are mainstream applications. There are benefits to installing solar PV and thermal systems on roof areas of existing buildings. Care must be taken in the analysis and best practices applied to avoid overestimating the quantities and value of the energy produced. Racking system configurations for solar PV arrays include fixed-pitch, single-axis tracking, and dual axis tracking. The type of racking and mounting systems used impacts the amount of electricity produced by the solar PV system [5]. An analysis for each type of configuration being considered is recommended. After successful

installation, routine inspections and maintenance are important to optimize power output. The variable production of solar PV arrays can be mitigated by using energy storage systems and interconnecting with the local electric grid.

Eventually, the solar arrays will require decommissioning at the end of useful life. When installing new solar PV and thermal systems, component recycling needs to considered [6]. It is becoming increasingly important to identify and use project components that can be more easily dismantled, sorted, and recycled.

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Data Center Mining and Natural Gas Generation

Stephen A. Roosa, Ph.D.

ABSTRACT

To support the growth of crypto-mining and artificial intelligence in the United States, companies have filed for permits to build new data processing centers. These data centers require substantial amounts of electricity that comes mainly from fossil fuel-fired generation. The larger ones may use as much electricity and a medium-size U.S. city. The inefficient use of fossil fuels is inherently counter to the idea of reducing greenhouse gas emissions.

Decarbonization has been identified as one of the top three trends in the energy sector [1]. The concept is transformative because it challenges us to transition from our present dependance on fossil fuels to more sustainable energy resources. Adding capacity to electric grids to meet the increased demand created by regional data centers has proved difficult. What are the alternative ways to provide electricity? Among the ways to provide this additional capacity is to use either renewables or nuclear energy. Regardless, natural gas is often chosen as a primary fuel to expand electrical generation in the U.S. This article explores the issues surrounding the use of natural gas to provide electricity for data centers and discusses their implications.

INTRODUCTION

Electric grid operators are seeing growth in electric demand due to the need for more air conditioning during summers, increased use of electricity by electric vehicles, and the growth in crypto-mining and artificial intelligence (AI). Data centers need large amounts of electricity

which presents new challenges with respect to electrification. The U.S., China, and the European Union were the global leaders in data center development in 2022, with facilities collectively consuming approximately 500 terawatt-hours (TWh) of electricity [2]. The largest data center markets worldwide by power consumption capacity are in the U.S. states of Virginia (with over 500 data centers), Texas, Ohio, and Georgia. Other examples of central locations for data centers include Beijing, China, and London, England. Together, these hubs have a combined capacity need of 5,404 MW [2]. Companies that are pioneering new data center development include Amazon, Microsoft, Google, Digital Reality and Equinix. The rapid expansion of central data centers is being driven by cloud-based applications, expansion of 5G infrastructure, alternative intelligence computing, research, and virtual collaboration [3].

In a world primarily energized by fossil fuels, data center growth creates numerous challenges. Think of data centers as a highly-concentrated electrical point load. Data centers only rarely generate all their power requirements from onsite generation. They require both alternating current (AC) and direct current (DC) electricity. AC is used for operations, cooling, and grid interconnections. DC is stored in batteries to provide redundancy and backup power during outages. Newly constructed hyperscale data centers require power capacities of at least 100 MW which amounts to an annual electricity consumption equivalent to that of more than 400,000 electric vehicles [2]. The electricity supplied must be reliable. The cost of downtime at data centers can average as much as $9,000/minute.

To support the growth of crypto-mining and expansion of AI in the U.S., companies have filed for permits to build over 1,200 new data centers. The global power consumption of data centers is forecast to more than double between 2022 and 2026 [2]. For the U.S., data centers account for about 4% of the nation's total electricity usage; that number is expected to climb to as much as 12% by 2028 [3]. The electricity needed for new and existing data centers is expected to increase from 325 to 580 TWh by 2028 [2]. Existing energy supply infrastructure is inadequate to support this scale of growth.

Consider the case of crypto mining. Without uninterrupted and inexpensive electricity, crypto mining is rarely profitable. For example,

crypto miners use about 150,000 kWh to unlock a single Bitcoin—enough to power 170 average U.S. homes for a month [4]. If the needed electricity was priced at $.164/kWh (the average U.S. retail price in June 2025), the total energy cost would be $24,600. The coin gained varies in value and is worth about $90,000.

Cryptocurrency mining operations are relatively mobile; their insatiable demand for electricity has driven crypto miners towards cheaper and dirtier energy resources including restarting inefficient and aging coal-fired plants [5]. There has been an over-reliance on the existing U.S. electric grids, drawing on excess and reserve capacities for energy supplies. In parts of the country where electricity costs are deregulated, the added burden of increasing costs is being spread to residential and commercial customers.

ELECTRICITY FROM CLEAN ENERGY RESOURCES

Where will this needed electrical capacity to support new data centers come from? Power generation is typically provided by fossil-fuel fired plants that use coal, natural gas, or oil. Others are supplemented by renewables such as hydropower, wind, or solar energy. While a fraction of the electricity is in some cases produced on site, most of the electricity needed for operations is normally supplied by the host utility grid which consists of the production, transmission, and distribution infrastructure. A key challenge is that data centers require 99.999% operations. This is difficult to achieve regardless of the energy resources used.

Some crypto mining operations are marketing their operations as eco-friendly yet green crypto mining remains an elusive proposition due to financial considerations and the large demand for electricity. These operations also need large amounts of fresh water which creates hurdles for their development in dry regions of the U.S. So far, it is evident that no true green crypto coin has yet emerged.

Renewable Energy Resources

The future of sustainable data centers requires collaboration, technological advancements, and decisive action to integrate cleaner

energy resources [6]. Some renewable energy resources, such as solar PV and wind power, can provide supplementary electricity when available. Alone they are unable to provide the consistent base-load power needed by data centers. Others, such as geothermal and tidal power, hold potential to provide baseload generation but are rarely applied.

Many data centers already use renewable energy, especially solar, wind, and hydropower. However, the resources are typically not owned by the data centers but by operators who supply power to the electric grid. Adding renewable resources involves infrastructure integration. Solar and wind power are notoriously variable. Renewables require space for equipment and locations where the use of the resources can be optimized. Locational mismatches are the norm. The locations with the best solar insolation may not be the best location for a data center nor near transmission and distribution infrastructure.

To harmonize the electrical loads using renewables, some type of energy storage system is often needed. For utility-scale energy storage, pumped hydropower offers a high turn-around efficiency. Other solutions include battery energy storage systems particularly lithium-ion or sodium-sulfur batteries.

Nuclear Energy

Nuclear reactors operate at full capacity more than other energy resources. The technology is designed to provide base load electrification. Nuclear plants operate 18 to 24 months at a stretch and refueling outages typically last only a few weeks. Regardless, a data center that relies solely on a nuclear plant may periodically require an alternative source of electricity.

There are no existing data centers that have their own nuclear reactors. In 2024, Microsoft and Constellation Energy reached a 20-year power purchase agreement to restart Three Mile Island Unit 1 to support Microsoft's data center operations [7]. Some companies are exploring placing data centers near existing nuclear plants for maximum efficiency and cost savings, including the Susquehanna Steam Electric Station in Pennsylvania and the Surry Nuclear Power Plant in northern Virginia [7]. Mirosoft and Meta are planning investments in nuclear energy to support some of their newest data centers. Google is planning

a 50 MW small modular reactor in Oak Ridge, Tennessee, to power its infrastructure expansion.

There are challenges associated with the use of nuclear energy. The up-front costs are substantial. Design, construction, and commissioning require long lead times. Licensing, demonstrating, and deploying additional reactors require years [7]. Efforts to add more power using behind the meter stations have been placed on hold by the Federal Energy Regulatory Commission over concerns that such deals could allow data centers to benefit from transmission systems without paying for them, potentially raising costs for utility customers [7]. The U.S. domestic supply of uranium fuel to power the reactors of the future is not in place—particularly for high-assay low-enriched uranium which is required for many advanced reactor designs [7]. Spent nuclear fuel rods must be cooled after being used in a reactor and stored (typically onsite) until a permanent disposal location is established.

CRYPTO MINING USING NATURAL GAS FROM ABANDONED WELLS

Data centers are needed to support crypto mining operations. They require vast amounts of low cost, high-quality electricity. Cryptocurrency miners typically use proof-of-work models and employ vast arrays of computers to solve mathematical problems to verify transactions and earn income. Many crypto mining operations use AI for energy optimization, predictive maintenance, market analysis, and real-time decision making. Crypto mining companies attempt to use public funds in the form of lucrative tax credits and the exercise of eminent domain to benefit their interests and advance their projects. They often claim to bring much-needed development, high-paying employment, and added tax revenue to rural areas.

What does data center development have to do with abandoned oil and natural gas wells? Electricity can be produced using turbines fueled with natural gas from abandoned oil and gas wells. The technology is proven and commercially feasible. This application provides an excellent example for a case assessment. Though a fossil fuel is being used, it

is often heralded by data center developers as having environmental benefits.

Background

Over the past hundred years, private landowners in partnership with U.S. oil and natural gas companies have drilled millions of wells [8]. When a well is no longer productive, most are abandoned and its operator moves on to richer deposits [8]. Drilling has left over three million abandoned oil and gas wells across the U.S. More than two million of these remain uncapped [9].

For most unproductive wells, the former owner(s) can be located. The term abandoned wells typically refers to those with a known owner or operator [8]. Being asset retirement obligations, they become a type of stranded industry liability [10]. Orphaned wells are inactive wells that are not reclaimed by the operators, have no identified liable party, and lack sufficient funding to cover the cost of environmental remediation and reclamation [11]. Of the total number of abandoned wells, about 125,000 are categorized as orphaned [12].

When not reclaimed, oil and natural gas wells create physical and environmental hazards. Not simply eyesores that present local environmental hazards, these abandoned wells gush millions of metric tons of methane—a greenhouse gas more potent than carbon dioxide over the time that it remains suspended in the atmosphere [9]. Plugging the wells prevents this and can reduce these fugitive emissions by as much as 99% [9]. These wells also pose risks of groundwater contamination by methane, brine, or other pollutants [11].

Reclamation

Reclamation is the process of restoring site stability and ecosystem functions. Disturbed lands are returned to their original use prior to disturbance, such as crop production, woodlands, or wildlife habitat. Well reclamation involves restoring the disturbed land areas to their natural state after oil and gas extraction has been completed and operations have ceased. After a drilling site has been safely abandoned, decommissioning involves removing as much infrastructure as possible from the site—this includes facilities, surface pipelines, wells, and related

drilling equipment [13]. This process involves environmental assessments, site and equipment decommissioning and removal, soil replacement, revegetation, inspections, etc. [13]. After a well reclamation certificate is granted the oil and natural gas company remains responsible for surface issues related to reclamation, such as topography, vegetation, soil texture, and drainage for 25 years, and remains permanently responsible for contamination and any infrastructure left beneath the surface [11]. The reclamation responsibilities for orphaned wells are borne by government agencies, the public, and taxpayers [12].

Laws typically require that after production ceases, all oil and gas wells must be permanently plugged if abandoned [10]. In the U.S., state programs have allowed companies to set aside funds for the future estimated cost of capping wells [9]. However, funding is usually insufficient to retire and plug wells left behind by bankruptcy. If industry is unable to pay the costs, then its lenders, investors, creditors, and ultimately oil-producing states are eventually forced to cover such costs [10]. The exact per well costs of reclamation are often unknown yet commonly understated. Liabilities for reclamation are calculated based on an average cost of $20,000 to $40,000 per well; the actual expected cost for a modern shale well can be as much as $300,000 [10].

If not reclaimed, landowners must live with the consequences of millions of unplugged wells. This problem is more pervasive on federal lands, where drillers are required to set aside only $10,000 for a single well with a maximum of $150,000 for all wells drilled nationwide [9]. Louisiana alone is estimated to have about 4,600 abandoned wells with cleanup costs estimated to be $650 million dollars, or $141,300 per well [14]. Newer wells are often drilled deeper making them more technically difficult and costly to reclaim [11]. Often well site reclamation does not happen.

Environmental Damage

The environmental damage from abandoned oil and gas wells goes beyond methane gas emissions. The wells can cause groundwater contamination and ecosystem degradation. Based on one study by the U.S. Government Accountability Office, the 8,050 at-risk oil and gas wells on federal lands are mostly in Wyoming with others in Colorado,

Montana, New Mexico, and Utah (see Table 1) [11]. Many have been inactive for over a decade. As time passes, site reclamation costs increase. These wells could cost up to $1.2 billion to fully reclaim—yet only an estimated $17 million is held in bonds for reclamation [11].

Table 1. Number of at-risk oil and gas wells on federal lands [11].

	Colorado	Montana	New Mexico	Utah	Wyoming	Total
Orphan Wells	100	15	0	61	2,317	**2,493**
Unreclaimed Wells, Inactive since 2015	537	497	529	385	3,609	**5,557**
Total	**637**	**512**	**529**	**446**	**5,926**	**8,050**

Abandoned oil and gas wells threaten local wildlife and their habitats. Over 5,000 at-risk well sites are in winter range or habitat restoration priority areas for big game animals [11]. Over 200 at-risk well sites are located on or near environmentally protected areas, including sensitive habitat for threatened or endangered species [11]. A total of 263 of these at-risk well sites are located within a mile of populated areas; 75 are located above the High Plains-Ogallala aquifer [11]. Held bond amounts are insufficient to fully cover modern reclamation costs. Abandoned or orphaned oil and natural gas wells are also found in Texas, Oklahoma, Pennsylvania, Kentucky, and Ohio. There are environmentally conscious ways to reuse abandoned well sites. For example, the oil and gas industry has been active in reclaiming sites by using enhanced oil recovery.

Crypto Mining Operations

To indicate support for efforts that advance decarbonization, some crypto miners propose using the residual natural gas from abandoned well fields for the purpose of electrical generation. The idea of using abandoned natural gas operations and associated wells to power cryptocurrency mining is relatively new [15]. Natural gas-fired electrification can use highly efficient combined cycle generators which is preferable from an environmental perspective than using coal.

Locating crypto mining operations at or near the generating stations reduces distribution and transmission costs and loads on regional grids.

However, many rural jurisdictions where abandoned natural gas wells are located lack zoning for data centers and regulations that directly apply to their operations are nascent [16]. While not the essence of their business model, crypto miners can avoid this complication by applying to be classified as a private utility company [16]. This enables them to generate their own electricity, operating essentially as an independent microgrid. Since they only rarely sell the electricity produced, many opponents argue that this is a poor fit for existing zoning ordinances [16].

Crypto mining at orphaned well sites is happening in Texas and South Dakota. The crypto miner's business model is to purchase old, inefficient wells, and extract the last bit of production from them to generate electricity for their operations [17]. The concept implies environmental benefits because the crypto mining operator is contractually required to cap the aging wells when they are completely depleted. This theoretically resolves the methane emission issue of site remediation. Unfortunately, many crypto mining operators fail to properly shut down and cap the natural gas wells, regardless of their commitments to do so. When their operations are no longer economical, they withdraw, and cease site activities, thus avoiding the costs of environmental remediation. Others file for bankruptcy protection prior to capping the wells as promised. This happens because the total cost of properly capping one natural gas well would likely far exceed the profit available from mining a single bitcoin.

There are numerous examples. Diversified Energy restarted the Longhorn Pad A site in Horton County, Pennsylvania, in 2022 using its remaining natural gas reserves to power a crypto-mining facility [15]. Prior to starting operations in 2022, the company neglected to obtain a state-mandated air quality permit which it did not receive until December 2023 [17]. Despite committing to plug 14 wells after operations ceased, the firm failed to do so after moving elsewhere, invoking concerns regarding its history of neglecting cleanup duties for aging oil and gas plants [17]. The wells it used were left open which violated its commitments and regional laws governing operations [17]. Diversified Energy separately agreed to plug 3,000 additional wells by 2034, but state officials indicated the company has not provided updates on their efforts [17]. Using future environmental benefits to justify development and failing to deliver is a

recurring problem in the data center industry. When the wells remain uncapped, the local stakeholders feel misled if not deceived. Rather that presenting an environmentally responsible public image, this constitutes a form of greenwashing.

Because of events like these some U.S. states are now against new energy-intensive crypto mining operations. Some argue that the high energy usage and electricity costs are ultimately subsidized by local consumers. This is because crypto mining owners are interconnected to a host electric grid which supplies power for peak demand. To attract development, industrial electricity tariffs are often lower than residential and commercial rates. A proposal for a facility in Oldham County, Kentucky, met with stiff public opposition during the site-selection process and was withdrawn from its proposed site [5]. LG&E, the local electricity provider, generates 84% of its electricity using coal, 15% from natural gas and only about 1% from renewables including hydropower [18]. It is arguable that because the crypto mining operation would have purchased electricity from LG&E, it would not have provided a green energy product.

Climate-conscious Approaches

The concept of using abandoned and orphaned natural gas wells to generate electricity for crypto mining operations in an environmentally appropriate manner is technically doable. Using energy efficient natural gas generators capable of capturing 98% of the leaking methane and using greenhouse gas offsets for any remaining fugitive methane emissions can be a workable and environmentally appropriate model [5]. Layering crypto mining into traditional oil and gas production operations could create additional sources of revenue for the industry [5]. However, while crypto miners may have digital programming prowess, they are not known to be environmental or energy experts. Effective regulatory policies must be in place else the power-hungry operators will simply abandon their sites when business conditions are no longer favorable.

By applying climate-conscious approaches, crypto mining at orphaned well sites can result in environmental advantages and support efforts that advance decarbonization [5]. Achieving this is difficult and costly if using natural gas from abandoned wells as the only resource

to generate electricity. Without remediating the pollution from the oil and gas wells, the failure to deliver environmental benefits (i.e., reducing emissions and site remediation) represents an abject form of industrial greenwashing. When fossil fuels are used to generate electricity, crypto mining cannot rightly be called a green energy solution. A better use of abandoned and orphaned natural gas wells is to provide peaking power in combination with renewable generation.

CONCLUSION

The rapid growth of data centers, driven by crypto mining operations and advancements in AI, overwhelms the demand for electricity [6]. The most advanced data centers and their AI microprocessors are useless without consistent and reliable electrical power. The question is how can their insatiable demand for electricity be met? Most are supplied with power using fossil fuel-based generation. What are the alternatives?

Vantage Data Centers is developing a project in Texas that will have a capacity of 1.4 GW [20]. While some point to the potential of improving data center energy efficiency, meeting the growing electric demand for electricity by improving their efficiency alone is unlikely. From 2016 through to 2022, efficiency gains in processing capabilities were offset by increasing power demand from data centers (see Figure 1). Afterwards this was no longer the case. Options to potentially improve energy efficiency include making use of the low-grade waste heat they tend to generate. Regardless, the electricity needed by data centers is outpacing efficiency improvements by a wide margin. Crypto mining and the increased use of AI are aggravating this problem.

Having exhausted efficiency improvements, the alternative is to provide more electricity. Natural gas generation reduces greenhouse gas emissions when compared to other fossil fuels. For example, OpenAI has agreed to develop about 4.5 GW of data center power for a cloud processing provider using natural gas generators [20]. As shown by the example of using natural gas abandoned wells to generate electricity, it is difficult to supply data centers loads without creating environmental issues.

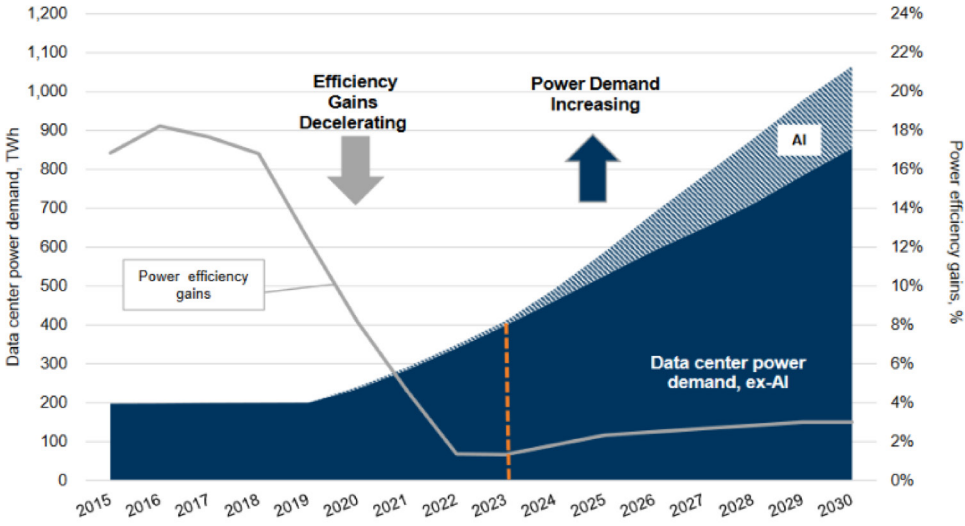

Figure 1. Data center power demand vs. efficiency gains (source: Masanet et al., 2020 Goldman Sachs equity research).

There are alternatives to using fossil fuels to generate electricity for data center operations. Using renewables and nuclear power is possible yet both present challenging development scenarios in real-world settings. Platforms that float on stable bodies of water (i.e., lakes or fjords) and use renewables may offer a scalable, mobile, and rapidly deployable alternative to traditional land-based data centers plus overcome the challenges of power constraints, land scarcity, and permitting delays [21]. In these scenarios, water for cooling is readily available. Small modular nuclear reactors have potential to supply power in some situations [22]. The use of utility-scale nuclear power, such as Microsoft's scheme to reopen Three Mile Island, offers another solution. However, U.S. uranium production is minimal so this option does little to enhance U.S. energy independence.

Unresolved Conundrums

Regardless of potential alternatives to supply electricity, the powering of data centers and their development present unresolved conundrums. Comprehensive solutions are needed. Achieving this is conceivable using a mix of enhancement initiatives and sustainable

energy resources. Carefully studying data center site locations is an important first step. Locating data centers in cooler climates near large bodies of water (e.g., on the shores of the Great Lakes) will ultimately reduce their energy loads and operations costs. Using sites at or near renewable generation potential is an important consideration. Some of the better schemes involve the use of hybrid electrical generation platforms to resolve issues due to variable capacity.

The question remains as to how the electricity will be generated. Microgrids may offer solutions for some big data sites. To support data centers, they could be designed as private electric grids. The Hypergrid, near Amarillo, Texas, aims to integrate nuclear, natural gas, solar, and wind power sources for AI data centers generating as much as 11 GW [23]. There are numerous examples of data centers that provide some of their electricity using onsite renewable generation (e.g., roof-mounted solar PV systems). Research and demonstration of package nuclear energy technologies is another pathway. Battery energy storage systems have a role as do systems that enable longer term storage capacity such as pumped hydropower.

A more radical alternative is to use prefabricated, modular data center units in a decentralized configuration that are linked together in a data networking configuration. In this way, they could use excess electricity that is available locally on the host electric grid or generated nearby using renewables.

If the electricity can be generated, new infrastructure will be required for distribution and transmission. Despite the centralization of data center megaprojects, most of the infrastructure is not yet available to support their widespread development. Updating the electric grids and expanding regional generation are the only reasonable options. However, years are required for the completion of electrification projects. Once in place and operating, there are mismatches between the lifespan of data center and crypto mining operations. Lifespan estimates of these businesses based on optimal operating conditions average from 3 to 5 years, a period during which the mining hardware is expected to operate efficiently without significant loss in performance or failure [19]. Realizing longer-term sustainable energy solutions for their operations complicates investment profiles. Solar and wind farms

have project lifecycles of 20 to 30 years.

Eco-friendly Data Centers

While some data centers use decarbonization to tout their sustainability and environmental initiatives, their operations are often linked to greenwashing schemes. Ultimately the responsibility lies on the data center owners and operators. They must find ways configure their facilities and operations to be more environmentally appropriate. An eco-friendly cryptocurrency mining operation that would focus on decarbonization might use renewable energy resources. They would employ best practices for electricity generation and use improved cooling systems that require less water consumption. Their development would focus on enhanced scalability, environmentally sustainable methodologies that reduce energy use, and prioritize lowering greenhouse gas emissions [4]. Initiatives might entail the use of more energy-efficient mining hardware, the exploration of alternative consensus mechanisms like proof-of-stake, and software systems that optimize energy allocation and use. Data center owners must also take financial responsibility for the needed electrical system infrastructure improvements.

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Peer Reviewed

The Opportunities and Limitations of Virtual Power Plants

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ABSTRACT

Virtual power plants (VPPs) can help mitigate electric load growth and provide power during times of need; however, in many applications they have limitations which have not been fully studied nor quantified. From a practical standpoint, VPPs often include a load, power source, storage system, and control mechanism that allows a system to minimize purchase power costs and potentially optimize grid power sales. Recent evidence shows the potential of utilizing virtual power plants to improve the reliability of larger power grids.

Virtual power plant applications have constraints which have not been fully studied. This research explores the opportunities and limitations related to VPPs. The U.S. state of Indiana was studied as a resource adequate zone for our illustrative example. Indiana was selected due to the potential of notable data center and manufacturing load additions. A zonal resource capacity expansion model of Indiana was developed using the standard industry model, PLEXOS®. This model included planned capacity additions, generation retirements, and generation repowers per recent Indiana utility integrated resource plans, stakeholder engagement forums, and other relevant public and proprietary databases. In addition, load forecasts, capacity expansion capital costs, operations parameters, and other relevant data were developed from a variety of public and proprietary databases across a robust set of scenarios. The selectable resources allowed for VPP additions were a mixture of smaller scale solar facilities and batteries.

For this study, the scenarios considered included a base case with moderate data center additions plus a high growth case with high data center additions. The latter scenario helps quantify the challenges of supplying uninterruptable data center power and/or replacing baseload generation with VPPs. A base case sensitivity allowed capacity expansion additions of combined cycle natural gas generation, gas peaking generation, and VPPs (assumed to be small scale solar and batteries) with 38 GW of installed resources in 2044. When the base case sensitivity was assessed only allowing VPP additions, the system had 62 GW of installed resources in 2044. A high growth case sensitivity that allowed capacity expansion additions of combined cycle natural gas generation, gas peaking units, and VPPs had 58 GW of installed resources in 2044. When the high growth case sensitivity was rerun only allowing VPP additions, the system had 218 GW of installed resources in 2044. Additional study parameters detailed within this research include yearly capacity additions by type, which shows the potential limitations of using purely renewable and storage-based VPPs to fulfill baseload energy needs.

INTRODUCTION

Virtual power plants (VPPs) are distributed energy resources that often include a load, power source, storage system, and control mechanism that allows for the minimization of purchase power costs and potentially the optimization of grid power sales. They provide communities and businesses a potential alternative to complete reliance on utility power purchases. In that regard, they can serve as a hedge against increasing power costs and price spikes if time of use rates apply. In addition, their distributed nature may improve total system effective load carrying capacity (ELCC). Other benefits include the potential reduction or deferral of transmission and distribution transformer and switchgear upgrades as well as reduced or deferred potential power line additions or reconductoring. As a small-scale distributed resource, random VPP outages are less impactful than the outage of a large thermal resource.

The potential to use VPPs as a reliability resource during times of need has been considered [1]. Pacific Gas and Electric demonstrated the

ability to utilize 535 MW of capacity from virtual power plants as solar generation output decreased into the evening [1]. This demonstrated the ability of VPPs to help accommodate the imbalance between peak demand and solar generation decreased evening output, also known as the "duck curve."

VPP application is adaptable to serve both residential and commercial loads, which typically have defined on- and off-peak behaviors. Industrial loads that can modify their production cycles may also have direct uses. VPPs, and more broadly microgrids, are finding applications related to residential, commercial, and some types of industrial systems [2].

The continuing growth of uninterruptible data centers loads associated with artificial intelligence (AI) applications, and current trends for retiring baseload coal generation, can cause difficulties in connecting these new loads to the bulk electric system. This can be challenging for a combination of renewable generation and energy storage to accommodate. This difficulty was presented in previous research [3].

Due to the rise of AI, many electric utilities are deferring baseload thermal generation retirements or exploring repowering of coal generation to natural gas. These initiatives help mitigate existing risk; however, they do not supply needed new capacity and generation. In many instances, these challenges have led to the deferral of new interconnecting loads. A shortage in firm capacity is also appearing in the independent system operator (ISO) capacity markets. Recently, the Pennsylvania-New Jersey-Maryland (PJM) ISO hit its capacity price cap as more generation was sought than was available on the market [4].

The need for new generation sources, and the desire to avoid having utility customers pay for potential stranded generation assets, is leading many data center developers to explore the option of providing their own resources as an alternative to relying upon utility purchases. These resources may be fully behind the meter or potentially interconnected to the host electric grid. AI data centers typically prefer their load to be uninterrupted. In the future it may be possible to configure training cycles around generation production schedules to periodically reduce or sequence loads to allow intelligent load resource matching. Also, data center developers may choose to leave part of their load interruptible and curtailed based on renewable generation production cycles.

To study the benefits and limitations of VPPs, Indiana was chosen as it has options for generation that include natural gas, renewables, and energy storage. Indiana has the potential for expanded natural gas generation and is expecting considerable data center growth. Recent utility integrated resource plans (IRPs) and stakeholder engagement forums have confirmed the potential rapid growth of projected data center additions within the state and the potential of utilizing comparatively cost-effective natural gas generation to supply much of the power needed [5-7].

Distributed Energy Resources and Transmission Expansion Projects

There is an increasing propensity for data center and other developers to provide their own generation resources due to capacity shortages. This can serve to lower the thresholds for load interconnections. These efforts are gaining increased importance as public utility commissions work to shield customers from the risks of stranded investments for generation and energy storage that are linked to speculative data center additions. The need for new generation has led to the possibility of expanding transmission systems to help accommodate new loads.

Distributed generation (DG) resources and distributed energy resources (DERs) are often an attractive and less costly option compared to constructing new transmission lines. While the expansion of the existing transmission system may benefit the reliability of the larger electric system, the economic advantages of transmission expansion projects tied to large scale renewable projects are often speculative. Legal challenges to transmission projects are impacting ISO sponsored transmission initiatives primarily linked to system reliability [8]. To successfully address these challenges, the reliability and economic value of transmission projects should be assessed across factors such as system transmission congestion benefits, generation curtailment reduction, reactive power flow, stability, and total system cost.

Because of these considerations, smaller scale distributed energy projects may have an inherent advantage over large-scale transmission projects in that they have fewer legal and regulatory risks. While the current federal administration has been skeptical of the benefits of

large-scale transmission projects, legal challenges for these projects are normally governed by the states [9]. In terms of development based upon load growth projections, small-scale DERs will likely continue to outpace large-scale transmission expansion projects.

MODEL BUILD

As a starting point for this research, the PLEXOS® capacity expansion module was used with the standard PLEXOS® Zonal 2025 Eastern Area Interconnection (EIC) data set. Indiana was separated from the rest of the model so that it could be independently studied as a resource adequate zone. For Indiana, known retirement dates for existing resources were updated along with new resource additions dates. These were based upon recent utility IRPs, stakeholder engagement forums, regulatory proceedings, and news announcements. Best engineering judgment was used to decide whether to utilize speculative retirement dates and incorporate uncertain generation and storage expansion projects. The same methodology was applied for existing coal generation that could potentially be repowered with natural gas.

The model was further modified to include multiple commodity forecasts which were partially based upon the 2025 Annual Energy Outlook from the Energy Information Administration (EIA) [10]. These commodity forecasts were paired with various load growth alternatives that distinguished between traditional load growth and hyper-scale data center growth. It was necessary to account for data center load shapes which are challenging for a combination of renewable resources and energy storage to accommodate. Other relevant factors such as a speculative carbon tax or cap were considered but not included for this analysis.

Model Assumptions and Restrictions

Generation and storage capital costs were developed from a variety of sources including, but not limited to, utility filed IRPs, stakeholder engagement forums, the EIA, and best engineering judgment. The capital costs used within the model for both combined cycle gas generation

(CCGT) and gas peaking generation (GPG) assumed that turbine demand and prices remained elevated across the planning horizon. The VPP resources that were considered include distributed scale solar resources and small-scale energy storage (Tesla Megapacks of 1.9 MW with 2-hour storage duration). The VPP resources were assumed to have a modest decrease in their capital cost over the planning horizon. The Federal Investment Tax Credit (ITC) was applied to the Tesla Megapacks as detailed within recent legislation. An ITC was applied to the distributed scale solar resources but was assumed to phase out by 2028.

Within capacity expansion modeling, solar and storage resources are often directly coupled in terms of a build ratio. This can restrict both storage and renewable additions as the combined aggregate cost can be uneconomical compared to allowing free selection of both resources. To this end, no restrictions on coupling between VPP solar resources and battery energy storage systems (BESS) were enabled in our analysis; no practical limitations on the total or yearly capacity additions of these resources were included. This also enabled BESS to be paired with peaking alternatives in that the capital costs associated with GPG in the model are a proxy for distributed gas generation costs.

Restrictions were placed upon the number of CCGTs and CPGs that could be constructed in a single year. In addition, the first-year new in-service CCGTs were available was set for 2030. These restrictions reflect ongoing supply chain restrictions for new natural gas turbines.

SCENARIOS AND RESULTS

The PLEXOS® capacity expansion module seeks to minimize total system cost subject to inputs and constraints such as capital costs, generator operation characteristics, fuel cost, the need to match generation to load, etc. The two scenarios studied in this analysis were a base and high growth case. The base case included moderate data center additions with assumed baseline growth for the non-data center loads. The high growth case included high data center additions with assumed high growth for non-data center loads. In the high growth case, the price

of natural gas-fired turbines was elevated relative to the base case. Both cases were assessed for three sensitivities: all resources (CCGTs, GPG, VPPs) allowed, only GPG and VPPs allowed, and only VPPs allowed. The VPPs were assumed to be distributed solar and small-scale batteries that had no practical limits on total capacity or yearly capacity additions. The natural gas peaking additions allowed in the second sensitivity can be viewed as a proxy for virtual power plants that include a combination of natural gas, solar, and energy storage resources. The results of this analysis are graphically detailed in Figures 1-6.

Figure 1 shows that in the base case sensitivity with all capacity expansion resources allowed the model tends to build a mixture of all available resources. CCGTs were the preferred resource; they are constructed early in the study period and available by 2030. In the later years, the model builds some VPP based resources as the capital prices for distributed solar and small scale storage resources degrades and the price of natural gas turbines remains elevated. For all scenarios and sensitivities, dispatchable resources remain prevalent due to coal to natural gas generation conversions. Early new natural gas generation is used to displace less economical coal-fired generation.

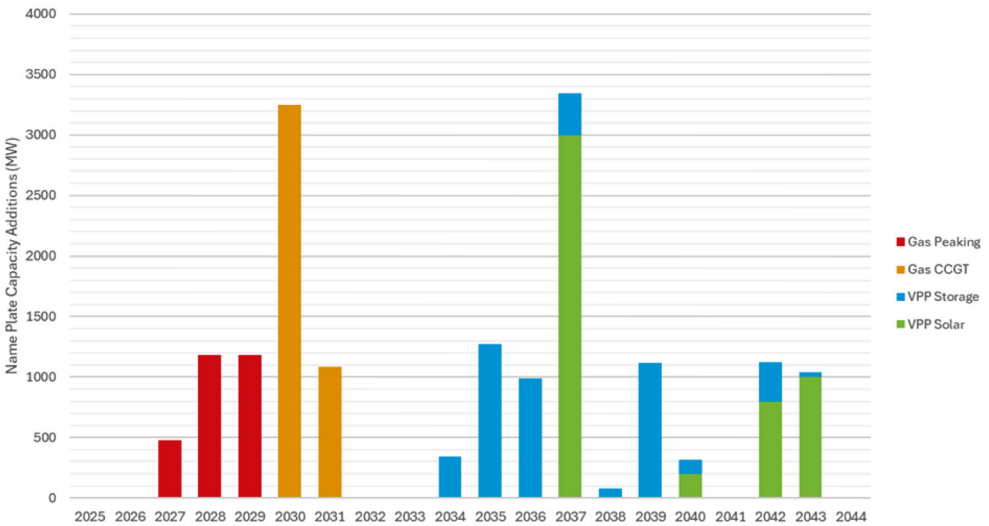

Figure 1. Base case capacity additions by year (all expansion resources slowed).

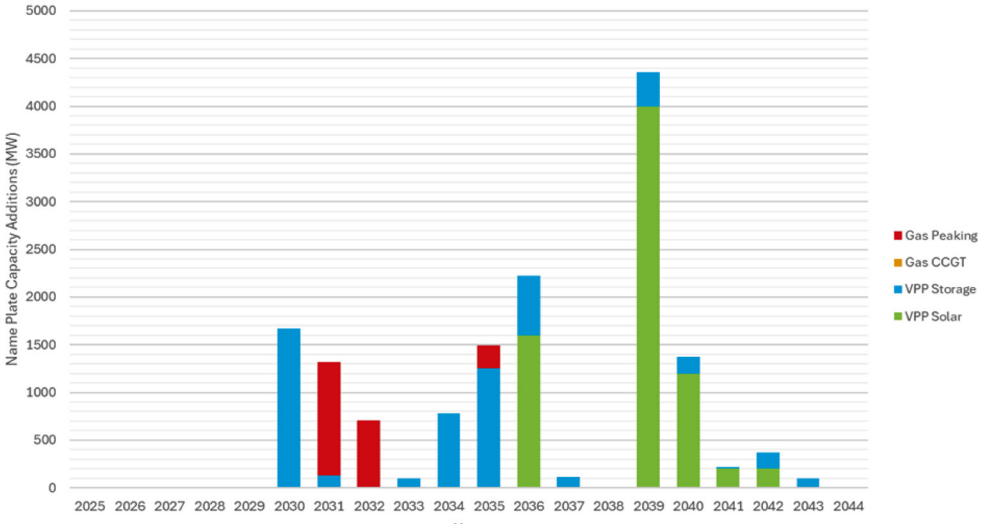

Figure 2. Base case capacity additions by year (only GPG and VPP capacity additions allowed).

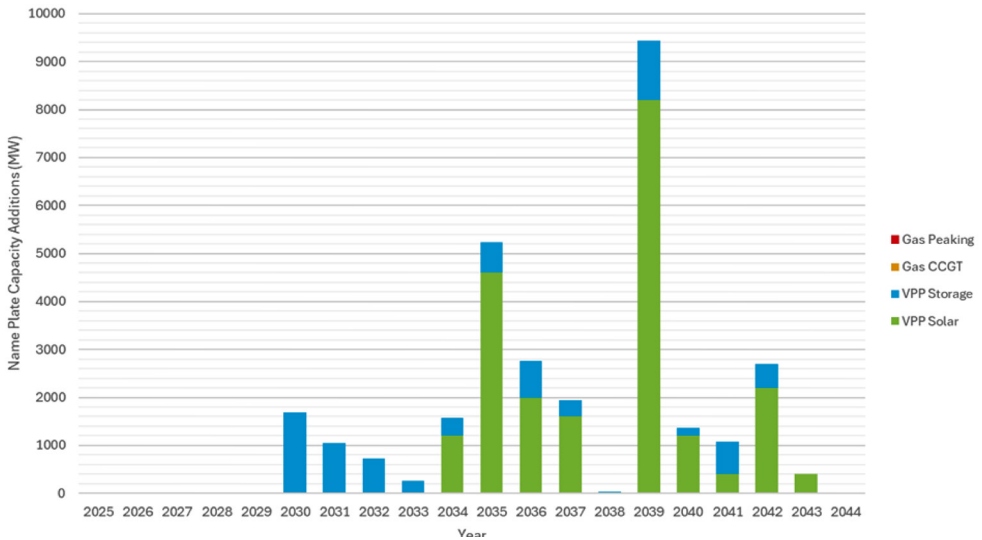

Figure 3. Base case capacity additions by year (only VPP capacity additions allowed).

Figures 2 and 3 show that the model defers the construction of VPPs until the model is forced to build them for resource adequacy. In both these cases, the model tries to defer constructing additional VPPs as the capital costs of distributed solar and small scale BESS resources degrades from year to year. In Figure 2 storage is paired with natural gas peaking resources earlier than it is paired with distributed solar.

Figures 4, 5, and 6 show a scenario where the large levels of total load growth overwhelm the existing dispatchable resources. Figure 4 is analogous to Figure 1 in that the model favors the early construction of CCGTs; however, given the shortage in needed resources, storage is constructed early before the CCGTs can be built. Figure 6 shows that VPPs exclusively utilizing distributed solar and small scale storage must be oversized in terms of name plate capacity additions to successfully match generation to load when no other resources are constructed. Natural gas peaking additions can be included within renewables and energy storage to lower nameplate capacity additions (see Figure 5).

Data Center Load Shape and Interruptible Load Impact

As demonstrated, data center load additions can be challenging for a combination of renewable resources and storage to accommodate.

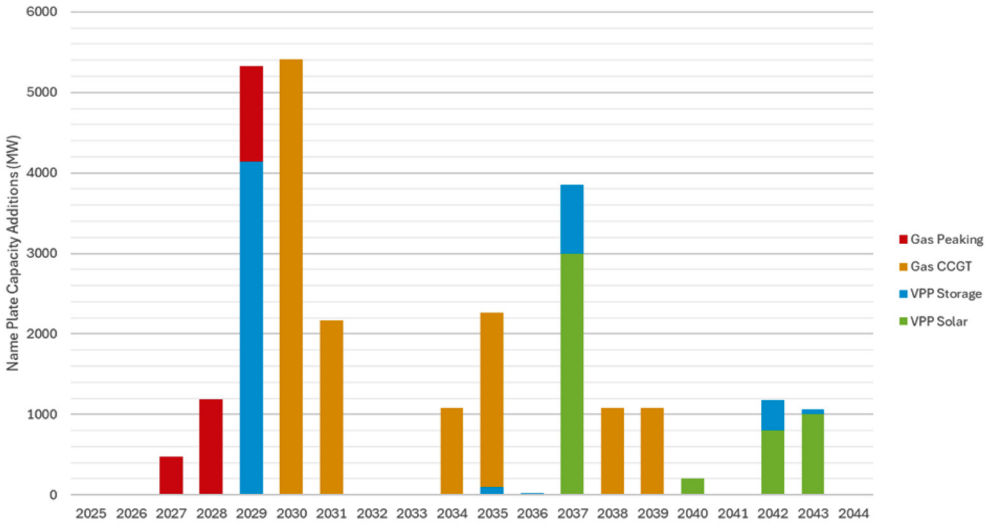

Figure 4. High growth case capacity additions by year (all expansion resources allowed).

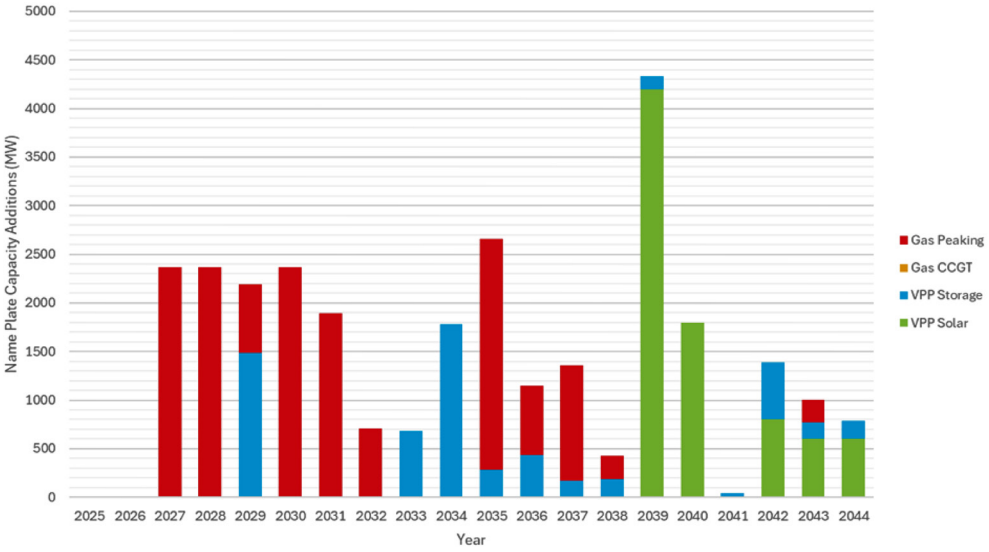

Figure 5. High growth case capacity additions by year (only GPG and VPP capacity additions allowed).

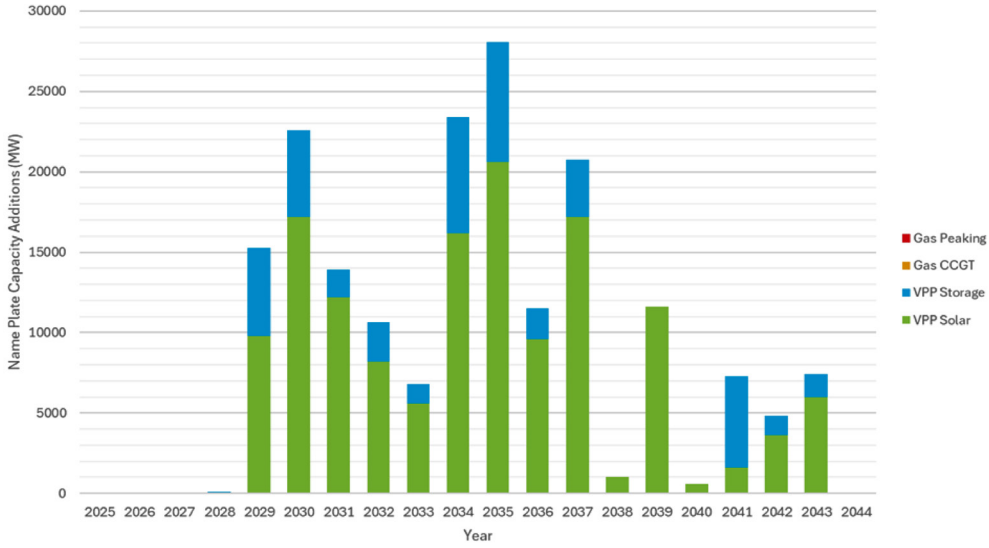

Figure 6. High growth case capacity additions by year (only VPP capacity additions allowed).

This is particularly true if the data center load profiles are assumed to be constant and uninterruptible. Supplemental analysis indicated that if the data centers are allowed to be interrupted or have a variable usage pattern that can be correlated to renewable output, the total name plate capacity of renewable and storage additions can be reduced. Due to continuing capacity and energy shortages, it is advisable that data center developers explore options related to demand response to improve new load interconnection prospects.

CAPACITY OBLIGATION AND ENERGY REQUIREMENTS

This analysis shows nameplate capacity additions relative to energy requirements. When dispatchable resources are dominant, nameplate capacity obligation and energy growth tend to track each other. Renewable resources, especially solar generation, tend to have firm capacity ratings that vary across the seasons. This is logical in that solar generation degrades during the winter. As indicated in Figure 6, total name plate additions when the model can only build a combination of distributed solar and small-scale storage exceeds alternative cases when natural gas generation is also included. To this end, it is important to compare the high growth sensitivities when all capacity additions are allowed relative to when only distributed solar and small-scale storage are allowed. Comparisons of total system name plate capacity vs. system peak load and system load vs. generation by year are shown in Figures 7-10.

As shown in Figure 7, when natural gas can be paired with renewable based VPPs, the model is largely able to match system installed name plate capacity to system peak load. When the model can only construct renewable based VPPs, it must overbuild installed name plate capacity by about 400% in the later years relative to the mixed case. In a similar manner, the renewable based VPPs require additional energy to charge the storage resources and increase total energy obligation, as is seen by comparing Figure 8 to Figure 10. These cases demonstrate that the focus on capacity in ISO marketplaces is relevant but future concerns must focus on energy rather than capacity if renewable installed capacity dominates installed thermal capacity.

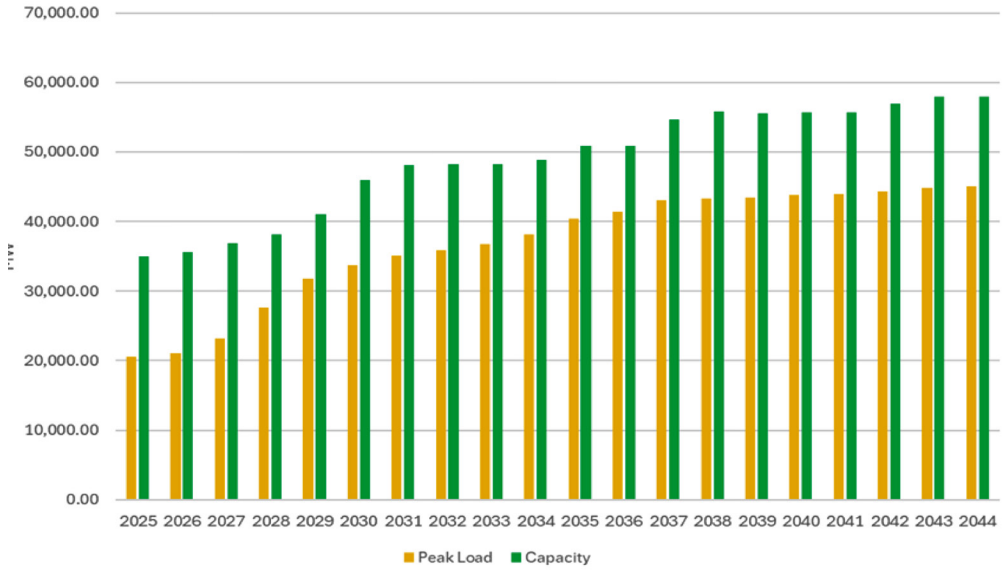

Figure 7. High growth case peak load vs. system installed capacity by year (all expansion resources allowed).

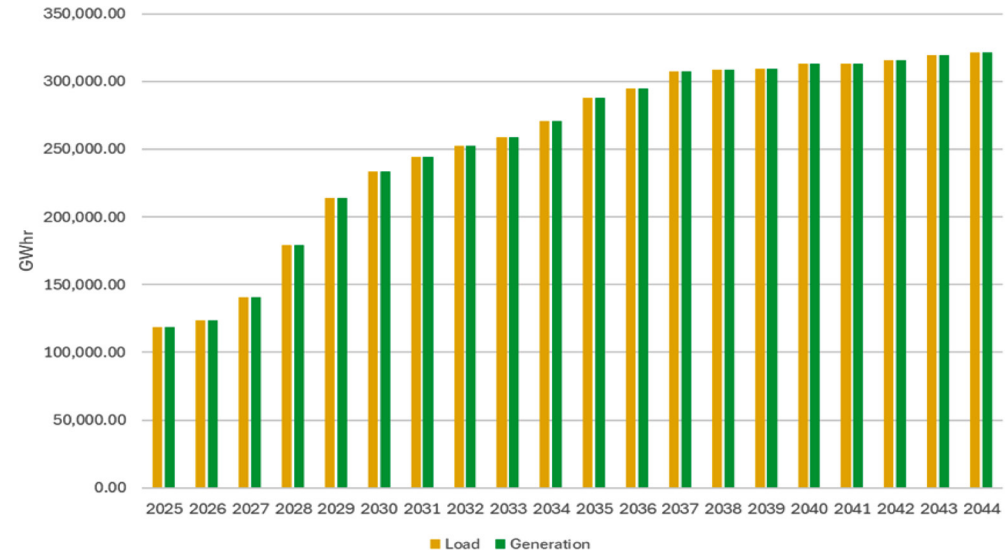

Figure 8. High growth case system load vs. generation by year (all expansion resources allowed).

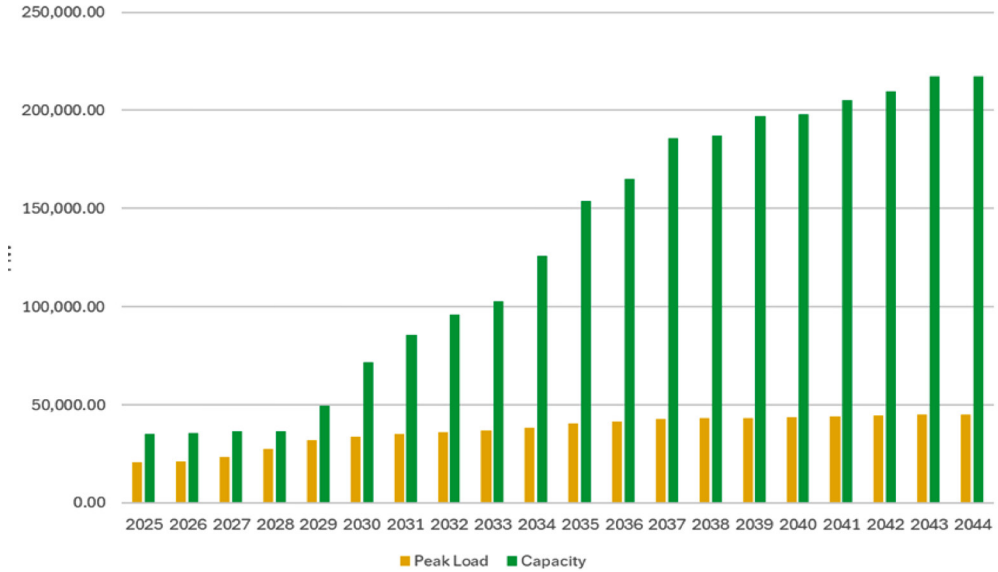

Figure 9. High growth case peak load vs. system installed capacity by year (only VPP expansion resources allowed).

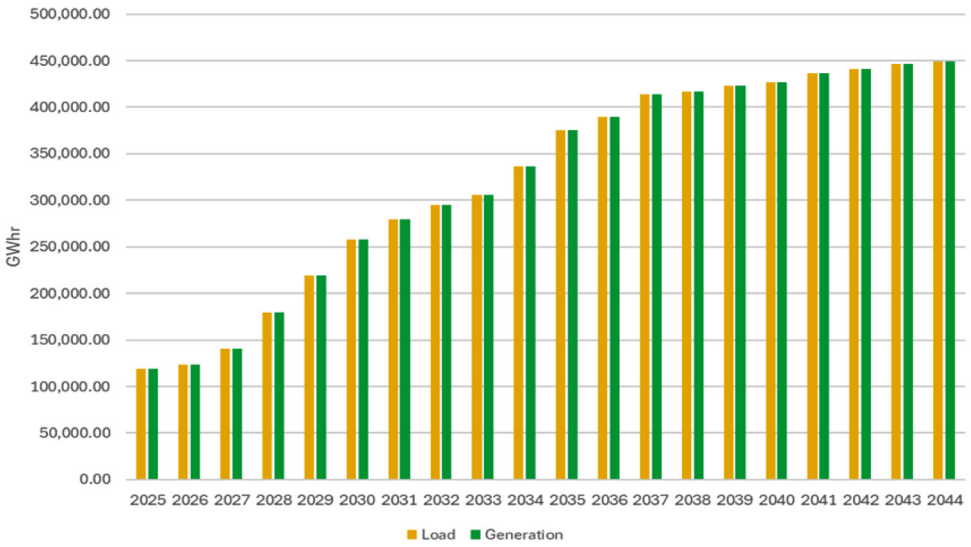

Figure 10. High growth case system load vs. generation by year (only VPP expansion resources allowed).

CONCLUSIONS

Virtual power plants are an increasingly important resource to the larger electric system. VPPs have been demonstrated to benefit total system reliability, but care is needed because their limitations have not been fully quantified. This research shows the challenges facing solar VPPs in accommodating large levels of load growth, especially when this growth includes significant levels of uninterruptible data center additions. The inability of solar VPPs to supply continuous output is a concerning limitation.

This research demonstrated that the limitations of solar VPPs can be overcome by incorporating strategic natural gas generation additions. Dispatchable natural gas generation, particularly larger combined cycle generators, can be used to supply data center additions and replace baseload retirements. The value of paired natural gas generation additions can be balanced against emission reduction targets to ensure system reliability at a reasonable cost to customers.

Note: Though affiliated, the views and opinions within this research are solely those of the authors and are not necessarily those of Ulteig.

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Methodological Framework for Solar PV Capacity Evaluation for Bifacial Systems Using ASTM E2848

Dhvanil Patel, Kajal Sheth, Shyam K. Sajev, and *Gautam Swami*

ABSTRACT

The solar photovoltaic industry uses several test methods to verify that installed systems meet outputs predicted by simulation models, with ASTM E2848 (updated in 2023) being the most widely adopted. This standard prescribes procedures for measuring and analyzing system capacity under natural sunlight at the installation site. It is commonly used for acceptance testing, direct and alternating current performance reporting, and ongoing monitoring. The goal of the capacity and modeled energy tests is to confirm that the integrated system achieves the guaranteed capacity and modeled annual energy production under site-specific weather conditions. This article presents a concise overview of the E2848 framework—its purpose and scope, test methodology, selection of reporting conditions, data requirements, calculation and reporting of results. It also discusses practical challenges, pass/fail acceptance criteria, cure-period procedures, sole-remedy implications for engineering, procurement, and construction contractors, and special considerations for bifacial irradiance.

INTRODUCTION

ASTM Test Method E2848-13 uses a multiple linear regression to model measured solar photovoltaic (PV) output as a function of plane-of-array irradiance, ambient air temperature, and wind speed over a short data collection window (typically 3 to 30 days). It then computes an expected capacity by evaluating that regression at defined reporting

conditions (RCs). While the approach is simple and convenient—especially for acceptance testing because RCs can be precomputed from historical meteorological data—it is more weather-dependent and can exhibit greater uncertainty than methods such as IEC 61724-2 unless care is taken to avoid extrapolation.

ASTM provides a methodology for selecting RCs to minimize extrapolation, though this may require defining multiple RCs for different seasonal conditions and complicate contracting. The standard addresses bifacial module behavior in capacity tests, where the measured power at RC (PRC) is compared to the guaranteed power at RC (P_{MIN}) to determine pass/fail (commonly expressed as $PRC/P_{MIN} \times 100 \geq 97\%$, subject to test uncertainty). In practice, P_{MIN} is established from a contractual performance model—often a PVSyst Pro-Forma 8760 simulation using specified inputs and meteorological assumptions or from validated external datasets. The contractual model and its assumptions produce the Pro-Forma 8760 dataset and may be amended as the facility design evolves, typically excluding soiling, snow losses, and unavailability. E2848 offers a pragmatic, regression-based capacity test that is applied for acceptance; it requires careful RC selection, uncertainty management, and alignment with contractual PVSyst modeling to yield reliable capacities.

PV CAPACITY TEST PLAN

No less than 45 days prior to the first day of the PV capacity test measurement period, a proposed PV capacity test plan shall be submitted to the owners' representative by the contractor for owners' representative review and comment. The PV capacity test plan includes the following information:

- The test procedure.
- A project model for PV capacity tests that assumes fixed soiling losses, zero unavailability, and module degradation in accordance.
- Proposed maximum soiling losses and with supporting details (e.g., soiling station analysis, date of proposed module cleaning prior to test, etc.).

- Proposed module degradation.
- Identification of the PV project under test: 1) number, make and model of PV modules; 2) array orientation; and 3) location (latitude, longitude, street address).
- Identification of interested parties, including contact information.
- The anticipated start and end dates of the PV capacity test measurement period.
- Identification of all sensors and transducers to be used, including cut sheets, calibration records, and map of sensor locations with sufficient detail to allow observers to locate the sensors and transducers. This includes sensors required for all applicable input parameters (meteorological station sensors, inverters, and revenue meter).
- Identification of supervisory control and data acquisition (SCADA) nomenclature for data channels, and any calibration parameters (default or custom) for those data channels.
- Identification of sensors intended for redundant measurement.
- Identification of multiple measurement formulas and weighting factors.
- The minimum number of redundant measurements needed to form a valid reading.
- Identification of SCADA data channels intended for use as an auxiliary parameter.
- Identification of known data quality concerns, such as time intervals when direct inter-row shading may be expected to occur.
- Time-stamp convention and data logger averaging technique and interval to be used for data reporting.
- An identified project model that includes software name and version, input assumptions, hourly output data, summary results, any post-processing steps needed to obtain final power estimates at the revenue meter, and a description of how electronic files are stored (for example all PVSYST, project file format, and Verge engine files needed to simulate annual energy).

ASTM TARGET TEST METHODOLOGY

There are four steps in the ASTM test methodology. Figure 1 provides a flowchart of the sequential steps of the methodology for PV capacity evaluation using ASTM E2848 in bifacial systems.

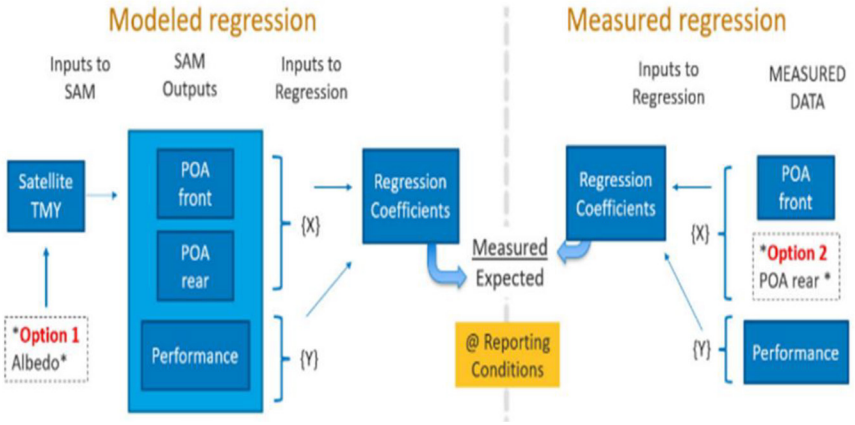

Figure 1. Flowchart diagram of the ASTM E2848 capacity test analysis.

Step 1: Gather Inputs and Data Collection

To avoid delays in conducting the test, the items required must be prepared. The following are prerequisites for conducting this test:

- A valid PVSYST model.
- Experience in regression modelling and a working test sheet.
- A properly operating system, with functioning equipment and calibrated weather stations.
- A minimum of 5-7 days of system operation to gather data; this is heavily dependent on weather conditions.

Step 2: Export Data

Take the inputs and prepare the data for analysis:

- Attain the PVSYST model and extract annual raw data. The raw data should include global horizontal irradiance, ambient temperature, wind speed, all correction factors relevant to calculating plane-of-array (POA) irradiance, plus a time and date stamp for each set of data points.

- Export climate and performance data from your data acquisition system. This raw data should include the date and time stamp, production meter, temperature, wind speed, and POA irradiance.
- Review the system's mechanical and electrical drawings. This will help the user determine if there are any peculiar issues that would impact the modelling, such as shading or severe inverter clipping.

Step 3: Filter Data for Quality

The most complicated aspect of the test is sorting the data to exclude low-quality or erroneous points. The data shall be filtered such that the minimum data requirements for site data are:

- 50 each 15-minute data points or 750 minutes of data.
- Exclude data below 400w/m^2 and at least above 98% nameplate capacity of the inverter.
- Reporting condition POA should be sorted in a range of +/−20%.
- There are technically no sorting requirements or limits for temperature or wind, but exclusions can be applied if they do not correlate with the performance.

Step 4: Perform the Statistical Regression

The regression model is performed to find the power capacity and the standard error of the regression measurements. If the ratio of power measured to power modeled is greater than 95%, and all regression errors are less than 5%, the test is valid with a passing result. When results are unsatisfactory, the most common pitfalls are:

- Depending on system design and season, it may take additional time to gather the required 50 valid data points that meet the test quality requirements.
- The test requires raw data from a PVSYST model that can provide the identified hourly requirements. The summary report from PVSYST is inadequate for this.
- Not running a proper regression. Even though the ASTM standard spells out the methods, it does not provide the tools to perform the analysis. Improper setup of the calculations is common the first time this test is attempted.

- Poorly calibrated sensors. The test is only as good as the accuracy of the measurements; it is critical to have the sensors properly calibrated prior to gathering data.

ASTM MEASURED SELECTION OF REPORTING CONDITIONS

Data collected in accordance with the above shall be used to determine the reporting conditions per the following procedure. A unique set of reporting conditions shall be determined for the fixed-tilt and tracking portions of the plant, according to this procedure.

For the plane-of-array irradiance measurements, the data recorded from multiple pyranometers will be averaged for each time interval for both the tracking and fixed tilt portions of the system.

- The calculation for the tracking RC shall use the data from the POA sensors mounted to the trackers; the fixed RC shall use the data from the POA sensors mounted to the fixed racking.
- If data from one of the pyranometers are excluded due to malfunction or sensor discrepancy, the data from the unexcluded pyranometers shall be averaged (in the case of malfunctions), or the data from all the pyranometers may be excluded (in the case of sensor discrepancy out of range of sensor accuracy).

The collected data set shall be filtered according to the following operations:

- The procedure described per section 9.1 of ASTM E2848-13 will be followed, except section 9.1.6, irradiance outside of range. All data identified by the applied filters shall be excluded.
- Any test data points in which the power output of an inverter is recorded to be greater than 100% of the inverter's maximum output shall be excluded. Data points affected due to snow or frost coverage of the modules shall be excluded if any of the following apply: a snow depth sensor, other measurement equipment, or a visual inspection that is supported by photographic data. There is a

difference between actual and expected output based on statistical means or engineering judgment.

– After filtering, the resultant data set shall be used to determine the reference irradiance (Irr0) for the reporting conditions.

To determine the Irr0, the test data shall be sorted according to POA irradiance from highest to lowest and examined to determine the highest POA irradiance value for which there is a nearly equal distribution of data points in the range of the selected POA irradiance. This irradiance shall be considered Irr0. There shall be no more than a 40%/60% spread in the irradiance distribution, i.e., no more than 40% of irradiance data above Irr0 and 60% of irradiance data below Irr0, or vice versa. All test data where the irradiance is outside of the range of Irr0 plus or minus the irradiance band (Irr0 ± 20%) shall be excluded. The minimum value for consideration as the Irr0 will be calculated by using Equation 1:

$$Irr_{min} = 400\text{W/m}^2 \div (1 - Irr_{band}) = 400\text{W/m}^2 \div (1\text{-}0.2) = 500\text{W/m}^2 \quad (1)$$

Wherein :

Irr_{min} is the minimum value for Irr0.

Irr_{band} is the size of half the irradiance band expressed as a number, a band of ± 20% is $Irr_{band} = 0.2$.

All irradiance values less than Irr_{min} shall be excluded from consideration as the Irr0. A value of 300 W/m^2 may be used in place of 400 W/m^2 if more data points are required. The maximum irradiance value for consideration of the Irr0 shall be determined by using Equation 2:

$$Irr_{max} = Irr_{high} \div (1 - Irr_{band}) \quad (2)$$

Wherein:

Irr_{max} is the maximum value for Irr0.

Irr_{high} is the highest irradiance value of the collected and filtered data set.

All irradiance values greater than Irr_{high} shall be excluded from consideration as the Irr_0. The filtered measurement data are defined as the resulting data set, and have a minimum of 500 data points.

- The 500 or more data points are under a one-minute data interval.
- If the filtered data set does not contain enough data, then the test period will be shifted per ASTM 2848-13 section 8.3.
- At the agreement of the contractor and owner, the irradiance band may be increased (not to exceed Irr0 ± 40%) or reduced (not less than Irr0 ± 15%) to obtain a necessary and reasonable number of data points.
- All data points with an irradiance less than 400 W/m^2 (or 300 W/m^2 if more data points are needed) shall be excluded.
- The average ambient temperature of the filtered measurement data shall be calculated. This average ambient temperature shall be the reference temperature (T0). This temperature may be different for fixed and tracking systems.

The average wind speed of the filtered measurement data shall be calculated. This average wind speed is the reference wind speed WS0. This WS0 may be different for the fixed and tracking systems. We use various formulations to calculate irradiance (G) and power (P) to test the different rear irradiance instrumentation methods. Details of these formulations are listed in Table 1, and the ASTM approach is illustrated in Figure 1.

Minimum Power Rating (P_{min})

The PV simulation model, as derived from PVSYST simulations, is used to establish the facility's expected annual energy output as measured by the inverters and confirmed by the revenue meter. The owner and contractor shall agree on all inputs to PVSYST to create the PV simulation model, including losses, weather data files, and component model files. The PV simulation model shall include separate outputs for the fixed and tracking portions of the plant. Each of the PV simulation model outputs must include, as a minimum, the following columns in the respective output.csv files (or 8760 files):

Table 1. ASTM E2848 capacity test input variables for each method.

Method	*Modeled Regression (Hourly average)*		*Measured Regression (15-min average)*		*Reporting condition*
	G Irradiance	*P Power*	*G Irradiance*	*P Power*	
Baseline (monofacial and bifacial)	G_{front} modeled based on historical weather data (NSRDB 2020), using DNI, DHI, albedo	Modeled power, from System Advisor Model (SAM), using historical weather data	Measured G_{front}	Measured power	Determined by PV CapTest defaults, based on ASTM E2939: 60th
1	G_{front} modeled based on field-measured GHI, albedo, and DHI	Modeled power, from SAM bifacial model with hourly field-measured albedo			percentile of measured irradiance
2A	G_{total}l modeled from G_{front} and G_{rear}, where $G_{total} = G_{front} + \Phi * G_{rear}$. Based on historical DNI, DHI, and albedo weather data	Modeled power, from SAM bifacial model	G_{total}l = measured front $G_{front} + \Phi * G_{rear}$	Measured power	
2B			G_{total} = measured G_{total} with reference module, calibrated		

- Date and time (formatted with months, days, hours in separate columns).
- POA irradiance (GlobInc, W/m^2).
- Horizontal irradiance (GlobHor, W/m^2).
- Ambient temperature (T Amb, °C).
- Wind speed (WindVel, m/s).
- Near shadings beam loss (ShdBLss, W/m^2).
- Inverter loss due to low voltage maximum power point window (IL VSmin, kW.)
- Inverter loss due to power limitation (i.e., clipping losses) (IL Pmax, kW).
- Available energy at inverter output (EOutInv, kW).
- Energy injected into the electric grid (E_Grid, kW).

For this procedure, the target period is the mean of the 90-day period extending an equal number of days prior to and after the test period. For example, if the test period is May 1st through 6th, then the target period will be March 17 through June 17. The test period may be concurrent for the fixed and tracking portions of the site. The minimum power rating (P_{min}) at the reporting conditions is determined from the PV simulation model for each of the portions of the site in accordance with

the following: filter the 8760 file for the plant to only include data within the 90-day target period and apply the following filters to the resulting 90-day data file.

- Exclude any data points with beam shading values (ShdBLss) > 0.
- Exclude any data points where the inverter is not in 'peak power point tracking' mode, as defined in section 9.1.8 of ASTM E2848-13.
- Exclude any data with irradiance values outside of the range established.
- Data points with POA irradiance < 400 W/m^2 (or 300 W/m^2, whichever is consistent).

After filtering, the resulting dataset shall have 50 or more data points. If less than 50 data points remain in the set, then the test period shall be shifted and a new target period shall be selected.

For the filtered target period dataset, a regression analysis shall be performed on the POA irradiance, ambient temperature, wind speed, and energy at the inverter output. The regression analysis is used to determine the regression coefficients in Equation 3.

$$P_{RCE} = (E + Eb)\,(a_1 + a_2\,(E + Eb)) + a_3 T_a + a_4 v \qquad (3)$$

Wherein:

a_1, a_2, a_3, and a_4 are the model coefficients,
Reporting conditions E is the POA,
Eb is the back POA x bifaciality factor,
T_a is the temperature, and
v is the wind velocity.

If all four model coefficients vary in the regression, the p-value for a_4 can exceed 0.05, indicating the influence of wind speed and poor statistical significance. In such case, the regression will be repeated keeping a_4 fixed at zero.

If modules are mixed bifacial and non-bifacial, the plane of array irradiance (BPOA) shall be scaled by the ratio of modules.

The minimum power rating (P_{min}) shall be calculated for each of

the portions of the site by substituting in coefficients *A, B, C*, and *D* and the appropriate reporting conditions (Irr_0, T_0, and WS_0) as shown in Equation 4:

$$P_{min} = Irr_0 \text{ x } (A + B \text{ x } Irr_0 + C \text{ x } T_0 + D \text{ x } WS_0) \quad (4)$$

Measured Capacity Ratio

The PV capacity test result is the ratio of measured capacity (*MC*) to the target capacity (*TC*), the measured capacity ratio (*MCR*).

$$MCR = MC \div TC \quad (5)$$

Performance Criteria

The performance criteria (*PC*) are calculated and expressed as a percentage using Equation 6.

$$PC = (P_{RC} \div P_{min}) \text{ x } 100 \quad (6)$$

If the performance criteria are greater than or equal to the guaranteed facility percentage, then the contractor has met the capacity guarantee.

Acceptance values of 95% to 97% of the mutually agreed upon simulation are common.

Capacity test = Measured power ÷ Expected power

Performance test = Measured energy ÷ Expected energy

Availability test = Measured operational hours ÷ Expected operational hours

Calculation of Performance Ratio

The performance ratio (as defined in future IEC 61724-1, 10.3.1) reflects the electrical energy generated relative to the amount of irradiation and the array direct current (DC) power rating of the plant. It is calculated using Equation 7.

$$\text{Performance ratio} = (E_{out}/P_0) \div (H_i/G_{i,ref}) \quad (7)$$

Wherein:

E_{out} is in kWh.

P_0 is the array DC power ratio in kW.

H_i is the plane-of-array irradiation in kW/m^2.

$G_{i,ref}$ is the irradiance used for ration the modules, usually 1 kW/m^2.

Acceptance criteria: The expected capacity (*PRC*) of the system shall be determined in accordance with ASTM E2939-13, Standard Practice for Determining Reporting Conditions and Expected Capacity for Photovoltaic Non-Concentrator Systems. This is accomplished by applying the performance model for the system used to generate the expected annual energy production estimate together with historical, typical, or actual meteorological data for the site at the same time of year as the test period.

The guaranteed capacity (P^G_{RC}) shall be the expected capacity margined by a contract tolerance of 3% as calculated using Equation 8.

$$P^G_{RC} = (1 - 0.03)\, P^E_{RC} \tag{8}$$

The system passes the capacity test if the upper confidence bound of the measured capacity is greater or equal to the guaranteed capacity or Equation 9 is true.

$$P_{RC} + \mathrm{U95} \geq P^G_{RC} \tag{9}$$

AC Losses

The alternating current (AC) side of the plant to be tested is from the inverter output to the power control center (PCC) power meter. The AC losses shall not exceed 2% of the power measured at the PCC power meter. These losses include mainly transformer losses and wiring ohmic losses. The losses are measured by subtracting the power measured at the inverter output from the power measured at the PCC meter. Power at these points shall be measured by means of the SCADA. These losses shall be recorded for 2 days. A test day will be considered valid only if there are no inverter or system failures, shutdowns, or interruptions.

Pre-test Conditions for AC Loss Tests

- Mechanical completion.
- Commissioning and reliability test successfully completed.
- Test schedule and plan reviewed and approved by the owner.

Inverter Test Description

The test procedures and schedule for the factory acceptance tests for the inverter shall include, at a minimum, the following:

- Burn in at design DC voltage at stepped loads, 25% increments.
- Verify clipping at differing simulated insolation values and DC input voltages.
- Validate efficiency at various loads at the design direct current input voltages.
- Simulate operation and performance at design environmental conditions of site.
- Verify the operation of inverter at voltage limits.
- Demonstrate that the unit will not be damaged during normal failure modes such as loss of power, loss of single AC phase, loss of DC input, or loss of communication link.
- Verify volts-amps reactive (VAr) power and power factor (PF) control of inverter at various conditions and phase voltages.
- Verify inverter operation up to 110% of rated power output.
- Demonstrate that inverters do not circulate current among phases or operating units.

Liquidated Damages

Performance liquidated damages are determined in accordance with the following formula:

(*A*) Guaranteed facility percentage (expressed as a decimal) minus

(*B*) the performance criteria (expressed as a decimal) multiplied by the contract price.

X = Capacity ratio is calculated as follows:

Measured capacity divided by guaranteed capacity (expressed as a percentage).

If X is less than 98%, capacity guarantee liquidated damages are payable by contractor to owner. The capacity guarantee liquidated damages = (97% − X) x (Contract price).

Cure period: If, when first tested, the test report does not meet the guaranteed capacity requirement, the engineering, procurement, and construction (EPC) contractors shall, upon reasonable notice to client, be afforded 30 days of unimpeded access to the system to undertake adjustments with the option to retest. During this period, the client shall ensure that: 1) the necessary third-party interconnections are continuously available; 2) the facility is operated as required to make the necessary adjustments and perform a retest; and 3) copies of the operational history of the system are available to the EPC contractor is illustrated in Figure 2.

Sole remedy: If the system does not satisfy the guaranteed capacity requirement when first tested, the EPC contractor, at its expense and sole option, shall correct such defect by repairing, replacing, and supplementing the power shortfall by providing additional modules as necessary to achieve the guaranteed capacity, per the initial design, or provide an equitable solution to compensate for the guaranteed capacity shortfall. The client is to provide sufficient space for the EPC contractor to use and perform supplemental remedies as necessary. If a defect in the

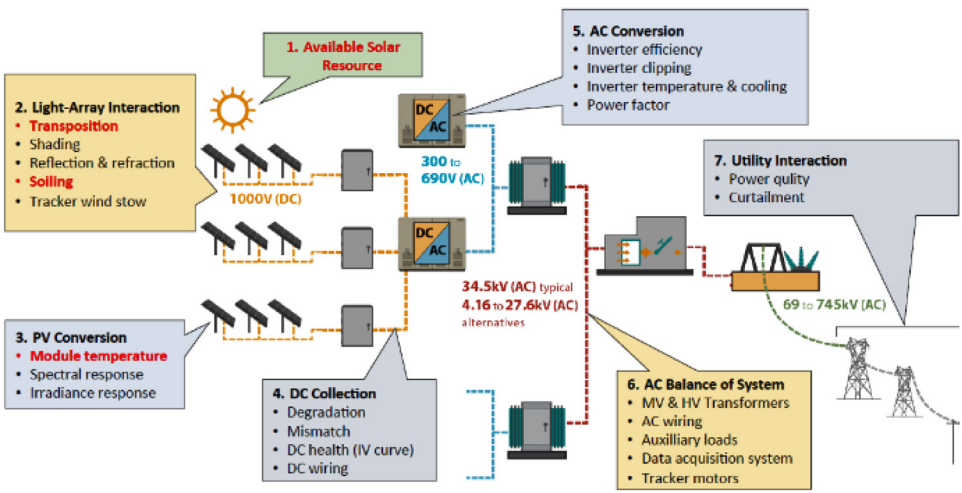

Figure 2. Site specific consideration.

equipment or part thereof cannot be corrected by the EPC contractor's reasonable efforts, the parties will negotiate an equitable solution with respect to such equipment. The remedies shall be exclusively the client's and the EPC contractor's sole obligations arising from such deficiencies. Such remedies may only be exercised by the client during the capacity test period.

CHALLENGES IN CONDUCTING CAPACITY TESTS

Inverter and plant clipping are common occurrences in modern PV solar systems, where the inverter or point of interconnection reaches its maximum power output, restricting the collection of critical data points. This issue is especially prominent during periods of high irradiance, often resulting in the exclusion of nearly all daytime data from capacity tests. Additionally, low irradiance levels in the winter months pose challenges to meeting the requirements of standard capacity tests. This problem is more pronounced in regions farther from the equator, where lower sun angles and shorter daylight hours make it difficult to collect enough data. External shading from topographical features or other obstructions further restricts valid data collection. Moreover, back-tracking during early morning and late afternoon hours causes rapidly fluctuating irradiance, which adds to the complexity of gathering reliable data.

Nonlinear Phenomena in PV Systems

Efficiency curves: Solar PV modules and inverters exhibit nonlinear efficiency curves, particularly at low irradiance levels. For example, PV module efficiency drops below 400 W/m², and inverter efficiency is only linear between 20% and 80% of its rated output.

I^2R losses: The resistive losses in cables and transformers, proportional to the square of the current, add to the nonlinearity but generally have a minor impact on the overall system performance.

Data scatter: Various factors such as rapidly changing irradiance, wind direction, and auxiliary loads (like tracker motors) can introduce scatter in the data, complicating the analysis.

Mitigation Strategies

Stowing trackers flat: By placing trackers in a horizontal stow position, the PV array behaves like a fixed array, flattening the power output curve and allowing more valid data points to be collected. This approach is especially effective when the system is likely to be power-limited at around 850 W/m².

Reducing DC capacity: Temporarily reducing the DC capacity by disconnecting some combiner boxes can prevent clipping and allow for the collection of valid data points. This requires scaling the results to reflect the full system capacity after the test.

Using high-resolution data: Collecting data at 1-minute intervals can capture more data points during ramp-up and ramp-down periods, which are typically excluded in lower resolution data (like 15-minute intervals). Although this introduces some error due to thermal time lag, it can provide a valid regression if carefully managed.

Expanding irradiance range: We suggest using a wider range of irradiance values, even at levels higher than 400 W/m², to increase the number of valid data points. This is particularly useful in winter when high irradiance values are rare.

CONCLUSION

ASTM E2848-13 remains an important standard for solar PV capacity evaluation, using multiple linear regression of measured power against irradiance, ambient temperature, and wind to estimate expected capacity at defined reporting conditions. The method is practical for acceptance testing but can be sensitive to weather variability and differences between historical and actual test conditions; this introduces uncertainties which are compounded by issues such as inverter/plant clipping at high irradiance, low winter irradiance, shading, backtracking, and the nonlinear behavior of modules and inverters at low light. Advances in simulation tools (e.g., PVSYST) and inclusion of bifacial module considerations improve predictive accuracy when combined with the ASTM approach; mitigation measures—stowing trackers flat, reducing DC capacity, collecting high-resolution data, expanding

the irradiance range, and strict equipment calibration and data management—help reduce uncertainty. Overall, when applied carefully and paired with robust modeling and quality control, ASTM E2848-13 provides a reliable framework for contractual capacity verification despite its inherent limitations.

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Impact of Unreliable Electricity Supply on Energy Efficiency and Economic Performance in Nepal's Steel Industry: A Case Study of Premier Steels

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ABSTRACT

Nepal's unreliable electricity supply, characterized by voltage fluctuations and irregular power availability, disrupts production and reduces the efficiency of Nepal's manufacturing, particularly in the metal and steel industries [1]. This analysis quantitatively assesses the impact of electricity unreliability on specific energy consumption (SEC) and economic performance in Nepal's thermo-mechanically treated (TMT) steel sector, employing a detailed energy audit of Premier Steels Pvt. Ltd. as a representative case study. The methodology integrates primary data, including electricity and thermal energy consumption, production logs, and outage records, with secondary data on sectoral production outputs and national gross domestic product (GDP). Data are used to develop a detailed energy audit and enable a comprehensive assessment of energy efficiency and economic implications under actual and counterfactual electricity scenarios.

Baseline analysis indicates that SEC under current electricity conditions (980.4 kWh/MT) exceeds potential SEC under uninterrupted operations (867.6 kWh/MT). This highlights efficiency losses attributable to production disruptions, equipment restarts, and reheating requirements. Scenario-based and sectoral extrapolations demonstrate that unreliable electricity supplies inflate the SEC-to-GDP

ratio by 13% to 15%, establishing a robust quantitative link between electricity reliability and industrial economic output. The findings suggest that improving electricity reliability could enhance capacity utilization in steel production, reduce reliance on imported TMT bars, and increase domestic output, while simultaneously lowering energy intensity and operational costs. To address these inefficiencies, this study identifies actionable interventions, including targeted electric grid modernization improvements to minimize unscheduled outages, deploy decentralized renewable energy sources for backup, incorporate demand-side management schemes to mitigate peak energy stress, and use energy audits to optimize operational efficiency. By establishing the first quantitative connection between electricity reliability and GDP in Nepal's steel industry, this research provides evidence-based guidance for policymakers to strengthen industrial resilience, enhance energy security, and support sustainable economic development. These results underscore the transformative role of reliable electricity as a high-leverage factor in improving industrial performance, reducing energy intensity, and fostering long-term competitiveness in Nepal's steel sector.

INTRODUCTION

Nepal's electricity supply has long been characterized by intermittent availability, poor power quality, frequent voltage fluctuations, and unexpected outages [2]. Although the government officially ended scheduled load-shedding in April 2018, industries continue to face recurring supply disruptions stemming from aging transmission infrastructure, seasonal variability in hydropower generation, and system overloads [1]. Such constraints disproportionately affect energy-intensive sectors like the thermo-mechanically treated (TMT) steel industry, a cornerstone of Nepal's industrial and infrastructural development. When industrial competitiveness is increasingly determined by operational efficiency, the relationship between electricity reliability and energy efficiency emerges as an important area of inquiry [3]. Enhancing energy efficiency is not merely a cost-reduction strategy but a fundamental determinant of industrial resilience, particularly in environments marked

by frequent supply-side uncertainties.

Manufacturing industries contribute approximately 5.3% to Nepal's gross domestic product (GDP); metal and steel industries represent nearly 18% of this sector [4]. The annual demand for TMT bars is steadily increasing, reflecting infrastructure expansion and growing domestic consumption [5]. However, Nepal's electricity system exhibits chronic unreliability. It is characterized by an average of 22 power outages per week which last from 11 to 171 minutes, voltage fluctuations, tripping events, and seasonal variability in hydropower generation [6]. These disruptions cause operational inefficiencies, including elevated specific energy consumption (SEC), production losses, equipment stoppages, process instability, diminished plant utilization, and increased reliance on imported TMT bars. The persistence of these challenges, despite national electrification efforts, underscore the systemic and structural issues within the energy supply sector that continue to constrain industrial development [7,8].

Empirical Assessments

Empirical studies in other national contexts underscore the multifaceted consequences of electricity shortages on industrial efficiency. Evidence from Chinese manufacturing firms demonstrates that electricity shortages influence technical efficiency, although adaptive responses can partially mitigate these effects [9]. One study employed data from 805 listed companies and applied stochastic frontier analysis, ordinary least squares, and instrumental variable estimation; it revealed the context-dependent complexity of electricity unreliability on industrial performance [9]. Research from Pakistan indicates that unexpected power shortages reduce annual revenues and the value added while increasing labor costs—highlighting the substantial economic ramifications of unreliable electricity in mechanized manufacturing [10]. A systematic review of global electricity shortages further identified consistent challenges, including production losses, increased operational costs, diminished investment, and reductions in labor income; mitigation strategies such as self-generation and renewable energy adoption were suggested to enhance industrial resilience [11]. Collectively, these and other studies emphasize the necessity of quantifying efficiency losses and

evaluating strategic interventions to counteract the adverse effects of electricity unreliability.

Both regionally and nationally, evidence demonstrates that Nepalese metal and steel industries face similar operational vulnerabilities. Investigations in steel factories indicate that electrical disturbances—including voltage dips, line trips, and load shedding—result in material losses, production delays, and elevated operational costs [12]. Complementary findings illustrate that power interruptions reduce financial performance by causing equipment damage, repair costs, and operational delays, thereby eroding profitability [13]. Nepal-specific assessments further reveal systemic challenges: a 2022 report by the Confederation of Nepalese Industries found that 64% of industrial establishments rely on diesel generators to cope with frequent outages, increasing monthly operating costs by an average of 5.3% [14]. Infrastructure limitations and management inefficiencies within the Nepal Electricity Authority exacerbate supply unreliability [14]. These national-level observations underscore the urgency of evaluating the operational and economic consequences of unreliable electricity supply in Nepal's TMT sector.

Benchmarking Using Energy Assessments

Benchmarking energy performance is central to understanding the efficiency of TMT steel production and the impacts of electricity unreliability. International studies provide SEC benchmarks that serve as reference points for evaluating plant-level performance [11,12]. Deviations from these benchmarks frequently coincide with periods of power instability, leading to idle energy use, repeated startup cycles, and process inefficiencies. Evidence from energy-dependent economies illustrates the vulnerability of industry to constrained electricity supply and demonstrates that power interruptions can reduce production, increase operational costs, and negatively affect GDP [15,16]. In this context, Premier Steels Pvt. Ltd. (Premier Steels) energy performance can be critically assessed against benchmarks to provide insights into micro-level operational inefficiencies and macroeconomic repercussions.

Unreliable electricity supplies disrupt industrial development in several ways. Energy-intensive industries have high SEC, production

losses due to outages, equipment stoppages, and process instability [1]. These disruptions lead to underutilized plant capacities, create reliance on imported TMT bars, and constrain domestic industrial growth. An energy audit at Premier Steels confirmed that supply interruptions increase operational inefficiencies and energy costs. Conversely, reliable electricity supplies reduce energy consumption and costs while enabling more stable production processes [17]. Quantifiable estimates of these benefits at the sectoral level in Nepal are limited. Given robust domestic demand for electricity, the possibility of power outages challenges local industries, further impeding the utilization of existing industrial capacity and perpetuating reliance on imports.

Gaps in Research

Globally, the nexus between electricity reliability and industrial performance has been widely examined, yet empirical evidence specific to Nepal remains sparse. Industry experts consistently identify unreliable electricity as a key contributor to production disruptions [1]; however, few studies have quantitatively assessed its impacts on SEC, production continuity, and sectoral economic contribution. This knowledge gap is particularly troublesome for the steel sector, where production inefficiencies and energy losses directly increase operational costs, limit capacity utilization, and reduce competitiveness in international markets.

Despite the growing body of global and regional literature, research gaps remain pronounced regarding Nepal's TMT steel sector. Firm-level operational and energy efficiency losses due to unreliable electricity supplies have seldom been quantified. The integration of energy audit data with production and financial records to calculate SEC deviations remains limited [12,14]. Moreover, the linkage between sectoral energy inefficiencies and national GDP contributions has not been thoroughly investigated [16]. Addressing these gaps requires a detailed, case study-based approach to precisely measure SEC, production losses, and the macroeconomic implications of enhanced electricity reliability. Such evidence is crucial for policymakers and industry stakeholders seeking to design effective strategies for energy efficiency, production continuity, and sustainable economic growth in Nepal's steel sector.

Assessing Electricity Reliability vs. Industrial Performance

To align with Nepal's 16th National Plan which has a goal of 100% of the population having electrification access [18], our study undertakes an in-depth energy assessment of Premier Steels to critically analyze the operational and macroeconomic implications of electricity unreliability. Addressing electricity unreliability in Nepal's TMT steel sector presents opportunities for industrial and macroeconomic gains. Enhanced electricity reliability could improve steel plant capacity utilization, reduce dependence on imported TMT bars, and strengthen domestic production, thereby supporting broader economic resilience. To achieve these outcomes, targeted mitigation strategies are essential, including grid modernization to reduce outages, deployment of decentralized renewable power, demand-side management programs to alleviate peak loads, and routine energy audits to optimize operational efficiencies [19]. These interventions reduce operational costs while enhancing sector production stability, energy efficiency, and competitiveness.

This study quantifies the potential impacts of unreliable electricity on the SEC-to-GDP ratio in Nepal's TMT steel sector. Using a detailed energy audit of Premier Steels, it assesses industry-level energy consumption, estimates production losses from outages, and evaluates sector-level implications. The research further examines electricity reliability effects on SEC, extrapolates findings to the broader TMT sector, and proposes strategies to mitigate supply disruptions. While focused on a single case, our study establishes the first quantitative links between electricity reliability and GDP in Nepal's steel industry. It provides evidence-based insights to inform energy policy, industrial efficiency, and sustainable economic growth.

METHODOLOGY

The research methodology illustrated in Figure 1 adopts a systematic, multi-level approach to analyze the impact of electricity outages on the SEC of Nepal's TMT steel industries. The process begins with data collection, integrating primary data from a case study using an energy audit of Premier Steels. These data cover monthly production,

electricity, thermal energy use, production losses, outage frequencies, and downtime. Secondary data are obtained from the literature and include national and international SEC benchmarks, outage trends, industry size, production output, and GDP contributions.

The next stage involves a case study SEC analysis, whereby the baseline combined SEC under a production-loss scenario is established. Then the combined SEC analysis is conducted under a no-production-loss scenario incorporating production loss estimations and outage variations. The study then proceeds to compare international and national SEC benchmarks, and develops scenarios correlating SEC with outage levels to identify the maximum, minimum, and average SEC, both with and without production losses.

Finally, the research advances to a sectoral-level analysis, extrapolating findings to the broader TMT steel industries of Nepal, linking SEC and energy consumption to GDP contribution of the TMT sector, and conducting scenario-based ratio analyses at the national level. The methodology culminates in the formulation of evidence-based policy recommendations, thereby bridging case-specific insights with sector-wide energy efficiency and resilience strategies.

Data Collection and Analysis

The data collection phase was divided into primary and secondary categories. Primary data were obtained through a detailed energy

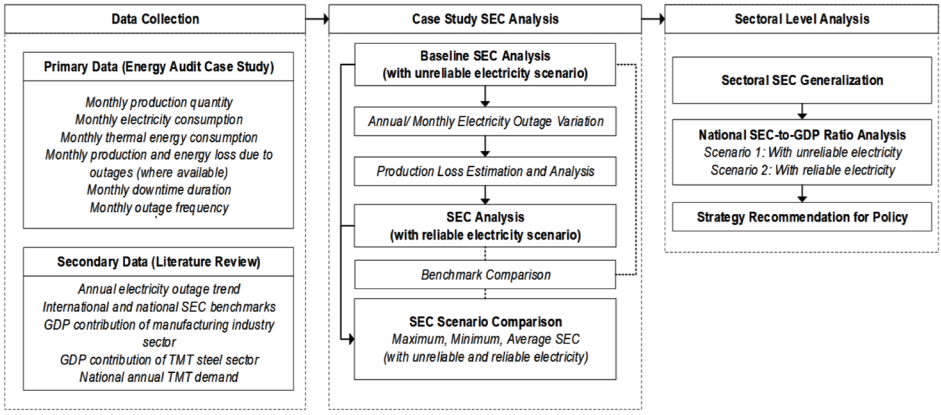

Figure 1. Research methodology.

audit of Premier Steel, a representative TMT steel industry in Nepal. The industrial operational records from July/August 2022 to January/February 2025) were analyzed. These datasets (compiled in Figure 2) include monthly records of TMT production quantities in metric tons (MT), electrical energy consumption from both grid and diesel generator in kilowatt-hours (kWh), and thermal energy consumption from furnace oil, expressed in kWh equivalent (kWh-eq). The collected data serve as the basis for calculating SEC under varying operational conditions. The greater use of electric furnaces highlights the industry's relative progress toward green steel production.

Secondary data were collected from relevant literature and institutional sources, encompassing national and international SEC benchmarks for the steel industry, historical outage trends, sectoral production outputs, and the contribution of the TMT steel sector to Nepal's GDP. These complementary datasets provide the foundation for comparative and extrapolative analyses at the national level.

The analysis of production losses warranted the need for annual electricity outage and frequency data. However, due to assessment limitations and unlogged annual records, the average monthly outage duration and frequency were calculated for the 2-month period prior

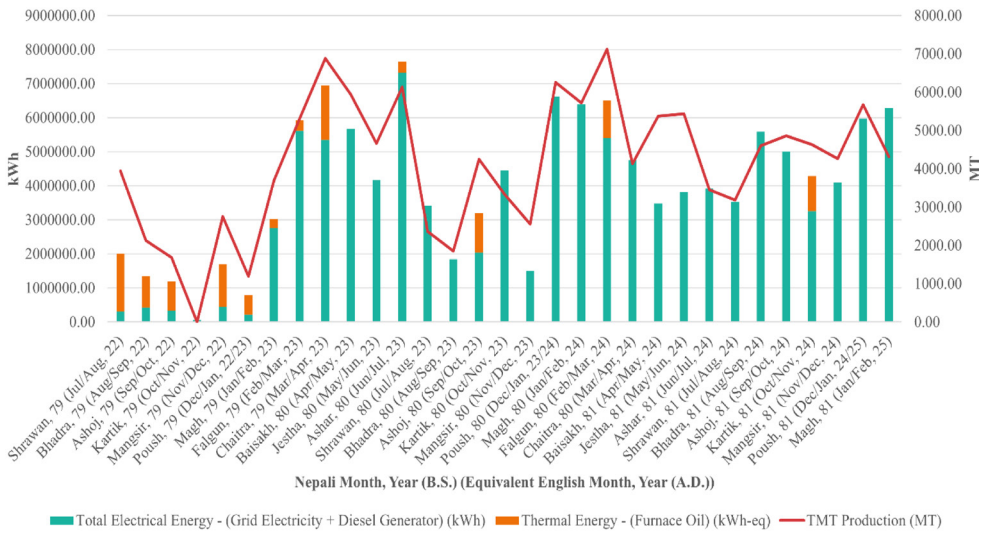

Figure 2. Input data.

to the study. The production loss quantities attributable to electricity outages for the two fiscal years were unavailable through industry records. This necessitated quantifying production losses and estimating monthly outage frequencies and durations for the 2 years. The monthly electricity outage frequencies for Nepal (a secondary data source) are provided in Figure 3 [6].

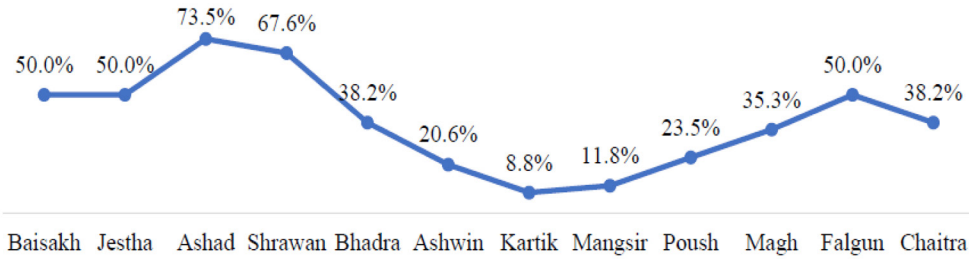

Figure 3. Annual electricity outage frequency.*

Case Study SEC Analysis

The baseline SEC was calculated using Equation 1, which accounts for both electricity and thermal energy consumption relative to TMT production output [20].

$$SEC_{C,b} = [\sum(EE_i + TE_i)] \div \sum PQ_i \quad (1)$$

Wherein,

$SEC_{C,b}$ = Combined specific energy consumption, baseline (kWh/MT)

EE_i = Monthly electrical energy consumption using grid electricity and diesel generator (kWh)

TE_i = Monthly thermal energy consumption using furnace oil (kWh-eq)

PQ_i = Monthly TMT production quantity (MT)

Based on the average outage frequency and duration recorded over two months and the annual outage frequency trend (see Figure

*The Nepalese calendar starts with the first month (Baisakh) on or about April 15th. The first day of Baisakh marks the New Year.

3), the monthly outage duration was estimated using Equation 2. The resulting production losses were categorized into two groups: 1) direct losses arising from the inability to operate during power outages, and 2) indirect losses, caused by lower molten steel temperatures that necessitated reheating.

Equation 2 integrates both outage duration and frequency, ensuring that the resulting estimates reflect not only the length of outages but also their recurrence. By normalizing recorded outage durations against the actual monthly frequency trend and the reference frequency, the method captures temporal variability while maintaining consistency with observed data. Incorporating annual frequency trends accounts for seasonal or operational fluctuations. Multiplying the adjusted outage duration by the hourly production rate provides a direct estimate of output losses in tons. For steel industries utilizing electric furnaces and continuous casting, brief interruptions necessitate reheating of molten steel, thereby reinforcing the equivalence between outage duration, lost production, and additional energy requirements.

$$OD = [\sum^{m}_{i}=1(AvOD_{r} \times AvOF_{i}) \div AvOF_{r}] \div 60 \quad (2)$$

Wherein,

OD = Average outage duration (hours)
$AvOD_r$ = Average outage duration of two recorded months (minutes)
$AvOF_r$ = Average outage frequency for two recorded months (nos.)
$AvOF_i$ = Average outage frequency (%)
m = Total number of months for which data was recorded (nos.)

The variations in monthly production losses were quantified using Equation 3. It incorporates various reference parameters including outage duration, hourly production rate (12.12 MT/hour, energy audit observation), the energy loss factor associated with molten steel cooling from 1,650°C to 1,600°C (30 kWh/MT), monthly production volume, and the energy intensity of the electrical furnace. The SEC of the electrical furnace was determined during the energy audit with data from 12 operational batches, yielding an average of 761.9 kWh/MT. This formulation establishes a systematic approach to estimate

production losses across multiple months by linking short-term observed outage data with long-term outage frequencies.

$$PL = \sum^{m}_{i=1} (OD_i \times HP) + \sum^{m}_{i=1} [(\mathrm{OD}_i \times F1 \times PQi) \div SEC_{ef}] \quad (3)$$

Wherein,

PL = Production loss (MT)

HP = Hourly production rate (MT per hour)

$F1$ = Energy loss factor for temperature decrease (kWh/MT)

PQi = Monthly production record (MT)

SEC_{ef} = Specific energy consumption of electric furnace (kWh/MT)

Assuming uninterrupted production, the potential SEC was calculated using Equation 4 [20]. This counterfactual benchmark enabled the assessment of efficiency losses attributable to electricity outages. National and international SEC benchmarks specific to the TMT industry were not available; thus, values reported for the broader steel industry were adopted as comparative reference points.

$$SEC_{C,p} = [\sum(EE_i + TE_i)] \div [\sum(PQ_i + PL_i)] \quad (4)$$

Wherein,

$SEC_{C,p}$ = Combined specific energy consumption potential (kWh/MT)

EE_i = Monthly electrical energy consumption using grid electricity and diesel generator (kWh)

TE_i = Monthly thermal energy consumption using furnace oil (kWh-eq)

PQ_i = Monthly TMT production quantity (MT)

PL_i = Monthly TMT production loss quantity (MT)

A scenario-based approach was used to evaluate the impact of electricity outages on SEC across two preceding fiscal years. Three scenarios were formulated to represent maximum, minimum, and average outage conditions. For each scenario, both baseline and potential SEC were calculated. This dual-case design facilitated the isolation

of outage effects and provided a comprehensive assessment of their influence on overall energy efficiency.

Sectoral Level Analysis

In the final phase, the case study results were extrapolated to sectoral and national levels using scaling techniques. The contribution of the steel sector to national GDP was evaluated in conjunction with sectoral SEC using Equation 5. This approach assessed the extent to which electricity outages in the steel industry affect national energy intensity and productivity indicators. For reference, Nepal's GDP was recorded at NPR* 5,348.5 billion in FY 2022/23 and NPR 5,704.8 billion in FY 2023/24 [21].

$$SEC{:}GDP = SEC_{c,a} \div SEC_a \quad (5)$$

Wherein,

$SEC{:}GDP$ = SEC-to-GDP ratio [(kWh/MT) ÷ (NPR in billion)]
$SEC_{c,a}$ = Average combined SEC, annual (kWh/MT)
SEC_a = GDP, annual (NPR in billion)

RESULTS AND DISCUSSION

Outage data were collected for the two months preceding the energy audit. During May 2024 the steel plant recorded 40 outages with a cumulative downtime of 218 minutes; in June 2024 there were 67 outages totaling 289 minutes. Lacking verifiable annual downtime data, the average of these two months (i.e., 53.5 outages with 254 minutes), was adopted as a reference for extrapolation. The monthly production loss trend was derived by combining this reference with the observed outage frequency pattern (see Figure 4).

The results indicate variability in TMT production losses across months, closely aligned with fluctuations in outage duration and frequency. Although a direct correlation between outage duration and

*1 Nepalese Rupee (NPR) = $.0071 U.S. dollars (USD) on 15 October 2025.

production loss is not always evident, relatively minor outages can lead to disproportionately large production losses. This indicates the sensitivity of steel production to electricity reliability (see Figure 4). The discrepancy in the fourth month is due to industry renovation, where production was halted. While production output varied seasonally, the consistent presence of outage-induced losses underscores the vulnerability of steel manufacturing to grid instability. These findings highlight the magnitude of efficiency constraints imposed by unreliable electricity supply and provide a quantitative basis for assessing their impacts on industrial energy performance.

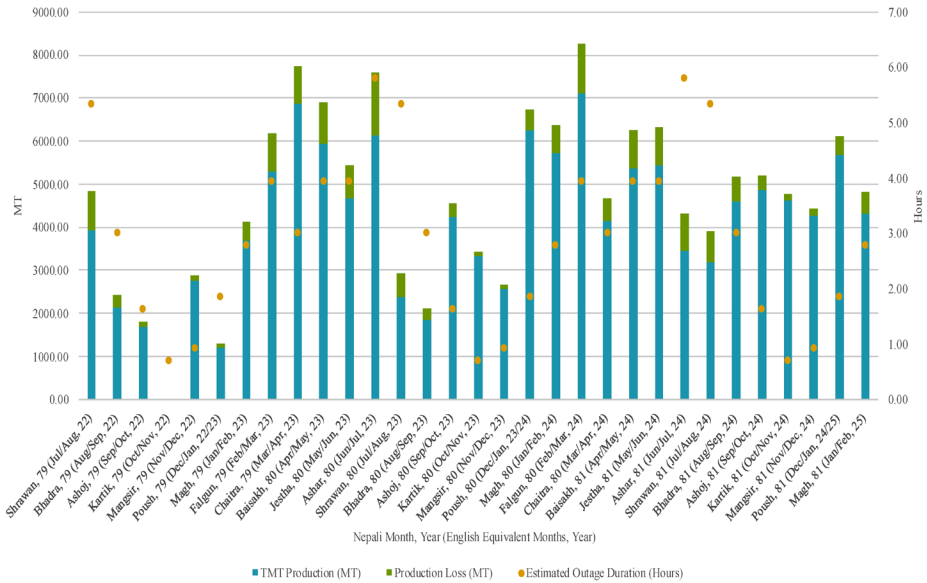

Figure 4. Estimated production loss distribution (July 2022 through February 2025).

Combined SEC Analysis

Figure 5 illustrates the monthly variation of baseline SEC alongside the potential SEC, the latter estimated by incorporating production losses as valid output. The comparison reveals that the baseline SEC consistently exceeds the potential SEC across the study period. This indicates the adverse impacts of electricity outages on energy efficiency. On average, the combined SEC was 980.4 kWh/MT under baseline

conditions; the potential SEC was reduced to 867.6 kWh/MT when uninterrupted production was assumed. This difference underscores the substantial efficiency gains that could be achieved with reliable electricity supplies, highlighting the sensitivity of the steel industry's energy performance to electric grid stability.

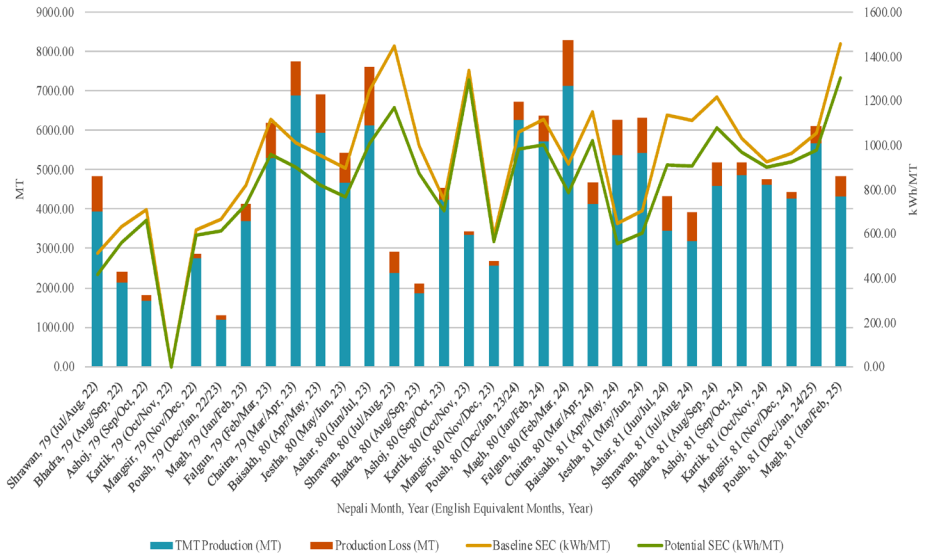

Figure 5. Baseline vs. potential SEC distribution (July 2022 through February 2025).

Benchmark Comparison and Generalization

Figure 6 shows the baseline SEC obtained from our case study (955 kWh/MT) was notably higher than the benchmarks previously reported for Nepal's metal and iron industries during 2012-2015, ranging from 560-700 kWh/MT [20,22]. This divergence reflects an increasing trend in SEC for Nepal's steel sector, which may be attributed to aging equipment, sub-optimal process integration, and higher dependence on electricity-intensive operations in the absence of modern energy-efficient technologies [1]. The reliance on outdated benchmarks for national comparisons appears less relevant to the current industrial context, underscoring the necessity of updated case-based evaluations.

The case study SEC remains comparable to India's TMT bar industry (i.e., 630 kWh/MT), though higher, suggesting potential

efficiency gaps that could be narrowed through targeted technological interventions. Conversely, the SEC is lower than values reported for Jordan (i.e., 1,700 kWh/MT), highlighting relative competitiveness in Nepal's steel sector despite structural inefficiencies [23]. These contrasts suggest that while Nepal's steel industries are not at par with regional best practices; they are better positioned than some global counterparts. Collectively, the findings affirm the case study SEC as a realistic baseline for Nepal and emphasize the critical need for efficiency improvements to align with international benchmarks and reduce long-term energy intensity.

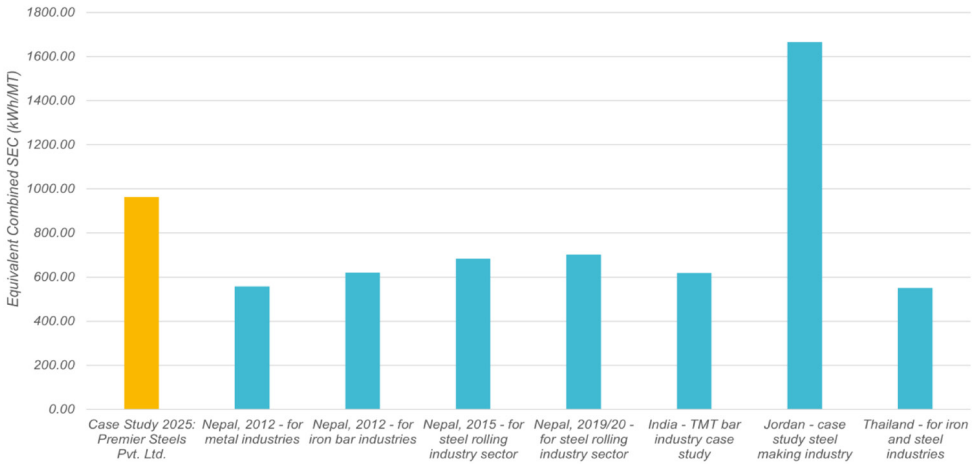

Figure 6. National and international SEC benchmark comparison.

SEC vs. Outage Level Scenario Development

The scenario analysis for FY22/23 and FY23/24 of Figure 7 highlights the strong influence of electricity reliability on SEC outcomes across poor, average, and best-case scenarios. In both fiscal years, SEC values are consistently higher during unreliable electricity supply conditions, with the gap between reliable and unreliable scenarios widening as outage severity increases. For FY22/23, the baseline SEC ranges from 510.8 to 1,246.7 kWh/MT, while FY23/24 exhibits a broader spread of 589.7 to 1,445.4 kWh/MT. This suggests greater sensitivity of production efficiency to outage conditions in the latter year.

The observed trend can be explained by the additional energy losses associated with frequent outages, such as equipment restart losses, production disruptions, and sub-optimal process operation. Reliable electricity scenarios demonstrate comparatively lower SEC across all cases, with 416.4 and 555.5 kWh/MT being the lowest values for FYs 22/23 and 23/24, respectively, underscoring the role of uninterrupted power in maintaining energy efficiency. Notably, the "poor" scenario in FY23/24 shows the highest SEC values, pointing to worsening grid reliability or higher production disruption costs compared to FY22/23. Conversely, the best-case scenarios in both years converge toward lower SEC values, emphasizing the efficiency gains achievable through stable electricity supply and optimized operations.

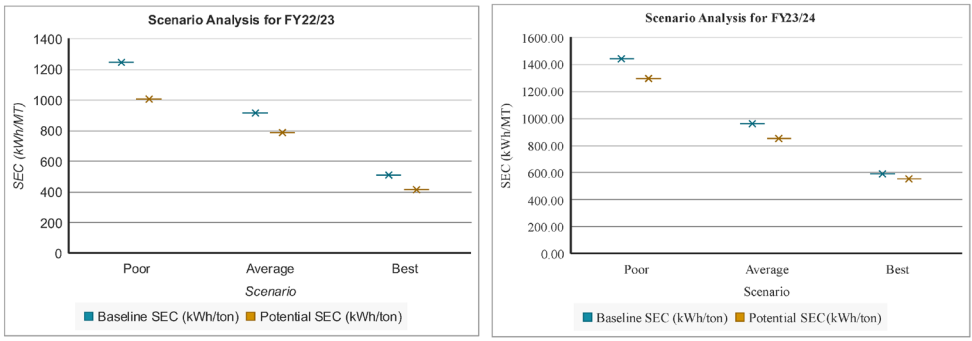

Figure 7. Scenario-based baseline and potential SEC comparison for FY22/23 (left) and FY23/24 (right).

Sectoral Level Analysis

The SEC-to-GDP analysis for FY22/23 and FY23/24, shown in Figure 8, reveals how electricity reliability influences the energy intensity of economic output. Nepal's GDP increased from NPR 5,348.5 billion in FY22/23 to NPR 5,704.8 billion in FY23/24. Under the baseline scenario, which reflects actual conditions with unreliable electricity, the SEC-to-GDP ratio declined slightly from 0.1708 to 0.1687 kWh/ton/NPR in billion. In contrast, the potential scenario assumes reliable electricity and full utilization of production capacity; it shows a lower SEC-to-GDP ratio, i.e., 0.1478 in FY22/23 and 0.1492 in FY23/24.

The results highlight two critical insights. First, unreliable electricity supplies impose a persistent efficiency penalty, inflating the SEC-to-GDP

ratio by roughly 13% to 15% compared to the potential case. Second, while GDP grew in FY23/24, the baseline SEC-to-GDP reduction was marginal, suggesting that economic expansion alone does not guarantee proportional energy efficiency gains. Instead, electricity reliability plays a decisive role in shaping the energy intensity of industrial output.

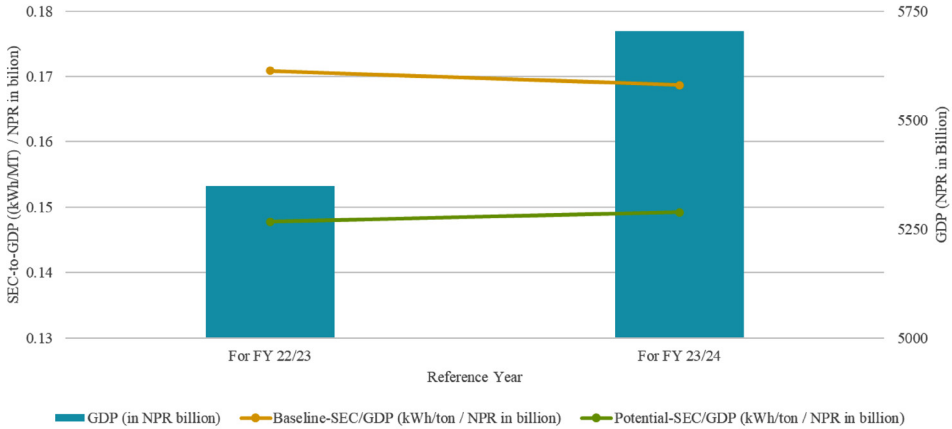

Figure 8. Annual GDP and SEC comparison.

CONCLUSION

This study provides the first quantitative evidence linking electricity supply reliability to energy efficiency and economic performance in Nepal's TMT steel sector. Using an in-depth energy audit of Premier Steels, the analysis demonstrates that unreliable electricity supply elevates plant-level SEC, increases production losses, and constrains capacity utilization. At the macro level, these inefficiencies translate into a measurable national energy-intensity penalty, with unreliable electricity inflating the SEC-to-GDP ratio by approximately 13% to 15% compared to a reliable supply scenario. The findings highlight that improved electricity reliability, alongside operational efficiency measures, could reduce SEC by 12% to 13%, thereby lowering industrial energy intensity and strengthening Nepal's economic resilience. These results underscore the importance of prioritizing grid modernization, decentralized renewable solutions, demand-side management, and

routine energy audits as central strategies for achieving sustainable industrial growth. Further advantages from the study could emerge in different technical and economic fronts, including: production capacity utilization, industrial energy efficiency, electrical technology adoption, sustainable industrialization, competitiveness with imports, export potential, investment attraction, per capita steel consumption, economies of scale, cost of production, trade balance improvement, GDP growth contribution, supply demand balance, and inflation control.

This study acknowledges methodological constraints, including reliance on limited outage data, a single-plant case design, and the absence of uncertainty or sensitivity analyses. These limitations suggest that while the findings are indicative and policy-relevant, the precise magnitude of sector-wide impacts should be interpreted with caution. Future research should expand to multi-plant audits, incorporate year-long outage monitoring, and apply probabilistic approaches to strengthen the robustness of sectoral estimates. Despite these constraints, our study makes a timely contribution to the literature and policy discourse, establishing electricity reliability as a decisive lever for reducing energy intensity, improving competitiveness, and advancing Nepal's broader goals of industrial electrification and sustainable economic development.

Acknowledgement

We extend our appreciation to Premier Steel Industries Pvt. Ltd. for providing technical support and access to operational data.

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