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*Journal of Energy and Power Technology*

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Research Article

# Monitoring Energy-Loss-Driven-Cost by Using Earned Value Simulation in Complex Systems

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**Academic Editor:** Erdem Cuce

**Collection**: Optimal Energy Management and Control of Renewable Energy Systems

*Journal of Energy and Power Technology*
2024, volume 6, issue 1
doi:10.21926/jept.2401004

**Received:** July 24, 2023
**Accepted:** February 01, 2024
**Published:** February 06, 2024

**Abstract**

The economic impact of energy loss stemming from end-user electricity consumption is a significant concern, with historical trends revealing escalating costs. Effectively managing both peak and off-peak demands remains a formidable challenge due to the unpredictable nature of consumer behaviors, leading to energy wastage. This study delves into the nexus of demand uncertainty, financial repercussions, and potential strategies to mitigate energy losses in the evolving landscape of electricity consumption.that causes financial loss. This simulation measure of time series data serves the purpose of determining what possibly contributes to policy and regulatory reforms and its notion as an economic growth pathway in Australia. The objective of this study is to build a relationship between social factors and financial aspects and discuss the issue of energy loss that emerges from the lack of leverage between end-users, providers and suppliers of electricity. Recognising the financial burdens associated with energy loss as electricity demand continues to rise, the investigation aims to elucidate the complexities underlying the difficulties in controlling these losses. The distinctiveness of the electricity industry, characterised by its prototypical nature, introduces dynamics that contribute to energy losses, thereby impacting electricity prices. Employing quantitative analysis, this research employs the Earned Value Method (EVM) tool to scrutinise the influential role of consumer behavior in precipitating financial losses. The study provides a comprehensive examination of the interplay between electricity demand and the adverse effects of energy loss during peak and off-peak consumption periods. Utilising time series data through simulation measures, the research identifies key metrics influencing the formation of electricity costs and prices. The findings not only contribute to a deeper understanding of the energy loss parameter but also offer insights into potential policy and regulatory reforms. With a focus on Australia, the research aims to establish a relationship between social factors and financial considerations, emphasising the issue of energy loss arising from the lack of alignment between end-users, providers, and suppliers of electricity. The study concludes by proposing pathways for economic growth through strategic interventions and collaborative efforts within the electricity ecosystem.

**Keywords**
SOS; energy loss; EVM; AC; EV; PV; CV

## 1. Paper Organisation

This study systematically organises the literature to construct a comprehensive theoretical framework, leveraging one coherent body of review. The primary objective is to establish a theoretical foundation for employing the Earned Value Method (EVM) simulation in addressing the intricate issue of energy loss within the context of electricity-driven costs. The literature review encapsulates an in-depth exploration of the electricity market and associated systems, with a specific focus on understanding the energy loss dynamics attributed to consumers. Within this framework, the research considers the intricate phenomena of electricity bidding and wholesale transactions, acknowledging their inherent uncertainty. A crucial aspect is the interconnection between these phenomena and the nature of demand, particularly the behavior and preferences of end-users. By delving into these intricacies, the literature review is strategically designed to uncover insights and bridge gaps in understanding the complex norms surrounding energy loss.

The overarching goal of the literature review is to provide nuanced answers to the multifaceted questions posed by the formulated problem of loss-driven costs. This entails a meticulous examination of the interplay between prediction phenomena, market structures, and consumer behavior, ultimately contributing to a more robust theoretical foundation for the subsequent application of the EVM simulation in addressing the research problem at hand.

## 2. Overview

The foundation of the electricity system rests on the acknowledgment of its inherently complex and dynamic nature, characterised by a challenging flow dynamic that resists precise control to specific supply points. The flow of electricity adheres to the path of least resistance, resulting in a reciprocal relationship where the operation of diverse electricity systems both influences and is influenced by various sources and regions. In Australia, territories are seamlessly interconnected through regional networks, fostering the economic sharing of generation. The functional boundaries of transmission and distribution networks are delineated within and outside National Electricity Market (NEM) jurisdictions [1]. Subsequently, the production and demand of electricity are intricately synchronised to instant changes, maintaining real-time system balance. Electricity transmission networks play a pivotal role in transporting bulk-generated energy from large generators over extensive distances to major load centers, operating at very high voltages ranging from 122 to 500 kV.

Figure 1 depicts the expected removal of generation capacity from the market, offering insights into the evolving landscape of electricity generation [2]. Distinct from many other industries, the supply chain of electricity from power supply to end-users is unaffected by inventories, and the commodity is primarily generated for immediate consumption with minimal storage considerations. Consequently, the volatility of electricity transaction costs is closely tied to changes in electricity costs based on end-users' consumption patterns. Most end-users settle electricity bills reflecting average costs over dispatch periods, often spanning a quarter or a year, creating a conflict with short-term demand management options concerning cost-reflective prices [3].

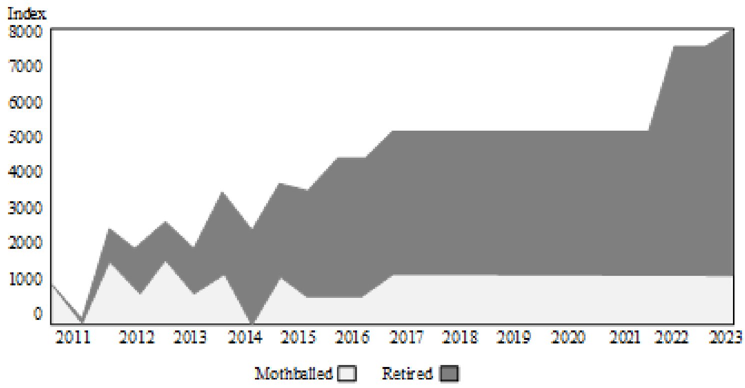


**Figure 1** Generation capacity expected to remove from the market [2].

Electricity rates exhibit variations across states and within the same state, primarily driven by generation charges that can constitute a significant proportion of overall electricity costs, resulting in variable usage charges. Figure 2 underscores the dominance of coal-fired power plants as a key player in electricity production in Australia, despite a temporary decline in 2014/15 [3]. The decrease in generation capacity, compared to the beginning of the century when coal's share exceeded 80%, highlights the enduring reliance on coal, still accounting for 63% of the total fuel used to generate electricity.

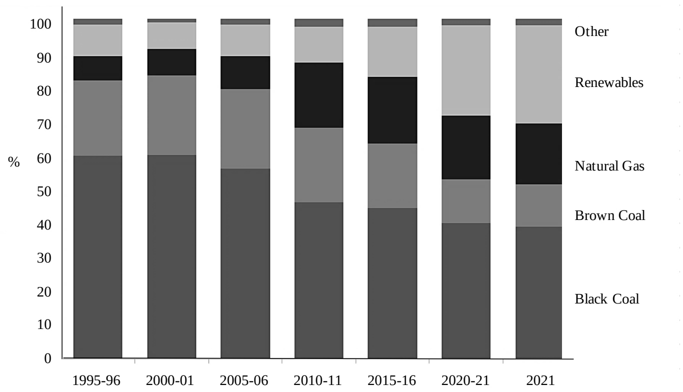


**Figure 2** Electricity generation: Fuel-mix.

Figure 3 delves into the renewable energy landscape, emphasising hydropower as a crucial source significantly affected by water shortages [4]. Despite being the highest renewable energy source, hydropower faced depletion due to droughts in 2000 and 2014-2015, reducing its contribution to 27%. The National Electricity Market (NEM) reflects a potential increase in electricity demand from both fossil fuel and renewable sources, supporting the growth of off-grid power. However, government priorities, especially in Large-scale Solar Generation (LSCG) projects at macro levels, have faced challenges due to the comparative cost of power generated from other sources.

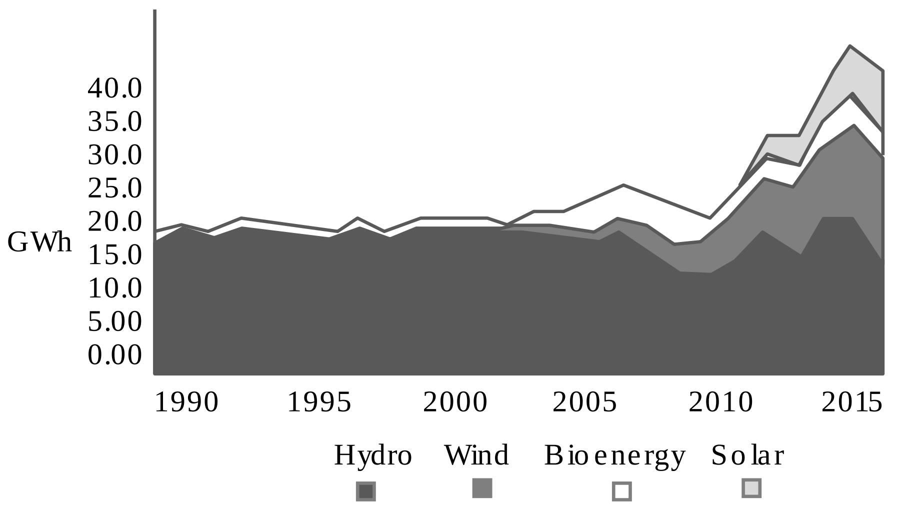


**Figure 3** Electricity generation: Renewable.

The electricity industry's vitality is intricately tied to diverse residential consumers and their integration into the market. A robust national energy policy adopting a portfolio approach, influenced by end-users' behavior, emerges as a key driver in the contemporary electricity industry. Recognising the imperative of avoiding energy misuse or losses, particularly among residential consumers, is fundamental for controlling energy market analysis costs. Continuous evaluations of electricity demands become crucial, alongside the need for reforming current policies, raising awareness of electricity demand, and identifying end-users' influence. Evaluating consumer demands for both renewable and traditional energy sources becomes essential for effective cost-benefit analysis, directing policy reforms to areas that promise optimal returns [5, 6].

This study provides a consolidated background to the Australian electricity market, aiming to understand the macro-micro relation and the challenges within the electricity supply chain. Before delving into conceptual models, the subsequent sections scrutinise the relationships between residential electrical consumers and other stakeholders, emphasising perceptions of the electricity grid system and energy loss.

## 3. Investment in Electricity

The intrinsic value within a grid system, marked by multi-generators and multi-users, is inherently distinctive and evolving towards sustainability. Recent strides in electric grid systems have propelled advancements, influenced by a myriad of factors both internal and external to the industry. Factors such as the operating environment, production economies, government intervention regulations, economic taxes, environmental effects, and energy loss play pivotal roles [7]. Energy loss, particularly associated with the distribution and generation of electricity, emerges as a significant factor influencing price disparities. This study delves into societal, economic, technical, and environmental aspects, with societal and ecological factors dominating the landscape. The research aims to explore societal factors contributing to losses in the electricity industry, emphasising the critical issue of energy loss. Independent systems analysis is provided to inform decision-making, shape system architecture, and navigate electricity trade-offs. The literature review establishes a comprehensive view, discussing factors influencing the formation of costs and prices. The study highlights the influential nature of consumer behavior, presents energy loss-driven solutions, and underscores the importance of policy and regulatory reforms within electric grid systems. Despite ongoing efforts to manage factors affecting operating costs and capital in electricity utilities, achieving complete control over the phenomenon of energy loss remains elusive [7].

Peak demand, representing the maximum electricity volume required at any point, establishes a rational connection between peak/off-peak demands and the reliability standards of network prices. Aging assets struggle to cover higher input and meet elevated reliability standards, contributing to rising network charges driven by electricity prices [8]. End-users, with a primary focus on residential houses, are expected to contribute to the smooth functioning of the net national product, control resource depreciation, and reduce environmental damage. However, assigning monetary values to external impacts on biodiversity and consumption qualities proves to be a complex and subjective exercise. Consumer demand behaviors, beyond the grid's control, constitute a controversial research topic, introducing uncertainties in valuing externalities related to human lifestyle, health, and climate change for various electricity generation technologies [6]. Recent Australian government projects target peak time control, aiming to reduce customers' payable electricity bills and extend benefits to the broader community, recognising the dynamic nature of residential consumers' habits [8]. An electricity grid system, functioning as a complex adaptive system (CAS), encompasses end-users, economic markets, physical networks, and diverse integrated agents [9]. Understanding the dynamics of consumers becomes pivotal for comprehending broader socio-technical transitions. Monitoring social practices is vital for shaping end-users' demands into more efficient forms. The transformation towards a smarter grid necessitates knowledge development and behavior change among networks and end-user groups.

This study focuses on the challenges confronting energy systems, emphasising the crucial role of the end-users' community in addressing societal causes of energy loss. This becomes particularly pertinent as the electricity industry increasingly transitions towards more renewable energy sources [4]. End-users purchase electricity based on negotiated-commercial-in-confidence rates, and contract estimates derive from commercially available information as depected in Figure 4 [4]. The use of 'spot market prices' is justified for future revenue certainty, considering the premiums paid based on hedging contracts to enter into long-term agreements [4]. This clarifies why the characteristics of end-users' demand in Australia are defined by multiple consumption bundles, denoted in cents per kilowatt-hour. Eligible consumers choose from various price or tariff structures for specific bundles, leading to the design of typical contract prices aimed at costing these bundles.

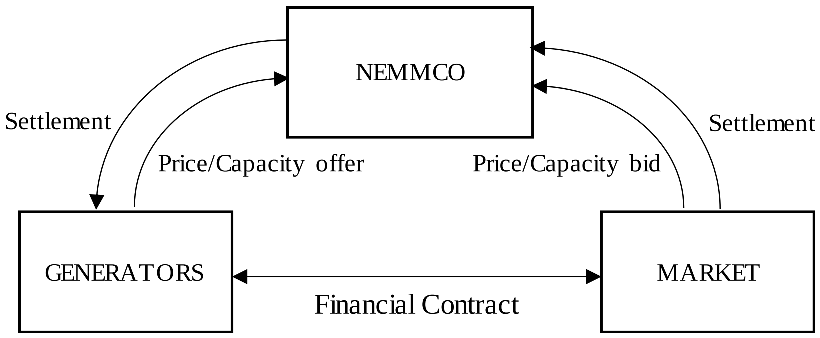


**Figure 4** National electricity market – settlement of electricity prices [7].

Figure 5 simplifies the flow of electricity and finances between generators, retailers, and end-users. Generators produce electricity, purchased by retailers from the National Electricity Market (NEM). Retailers, in turn, buy electricity from transmission network selling points and sell it to end-users via distribution points. End-users have the flexibility to choose electricity providers via a regulated standard contract price [10]. Contracts cover network costs, buying electricity from the wholesale market, and retail costs, with the weight of retailer prices varying within an average reach of up to 10%. The bulk of costs, up to 90%, includes network and wholesale costs, mainly driven by the network costs of generators, transmitters, and distributors connected to the NEM [11]. Electricity providers measure success based on cost recovery and profit generation. In this highly competitive market, with limited options available, companies face risks as expectations of turnover rise between none to small margin profit, leading to complex dynamics in sharing through different market terms like like "pass-on," "pool/spot price," "agreed price," or "strike price."

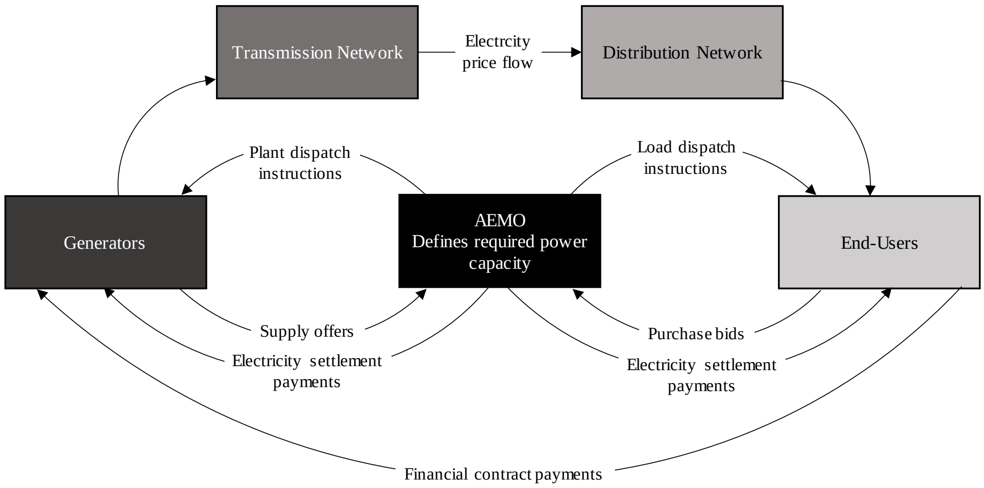


**Figure 5** Electricity financial cycle between generators and end-users.

## 4. Learning Curves of Costs Vs. Prices

The influence of electricity costs reverberates both directly and indirectly throughout market competition, impacting not only retailer businesses but also the industrial, commercial, and residential communities they serve. Framed as a qualified good with reservations for major barriers, electricity supply significantly contributes to economic activities. Examining electricity consumption as an intermediate input for production reveals its substantial role, accounting for 19.3% of total production, with unavoidable inputs such as coal, gas, and oil comprising 32.6% [12-15]. However, the challenge lies in managing energy loss and consumer behaviors to reduce costs in power generation plants, transmission lines, and distribution areas, ultimately fostering environmental sustainability and efficient home solar panel use.

Key aspects of energy loss, occurring when consumers and providers purchase additional electricity from the NEM, contribute to 'lost' electricity during transmission and distribution, intensifying losses at peak times. Approximately 12 billion kilowatt hours (TWh) are lost in the energy consumption sector and an additional 12 billion TWh in transmission lines. Historical data reveals a significant increase in electricity prices in Australia from 2008 to 2014, exceeding inflation by over 80%, as depicted in Figure 6. The primary driver for these increases is attributed to the costs associated with upgrading and maintaining the electricity network to meet end-users' demand, as shown in Figure 7 [8]. The cost breakdown in Australia and New South Wales (NSW) encompasses various factors impacting both generators and consumers, such as Base load coal technologies, Base load gas technologies, Lowest capital cost solar, and Lowest capital cost wind [16].

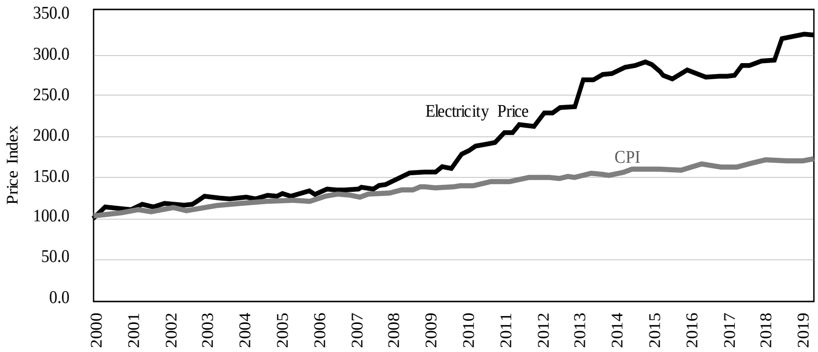


**Figure 6** Electricity prices & consumers' price index [9-12].

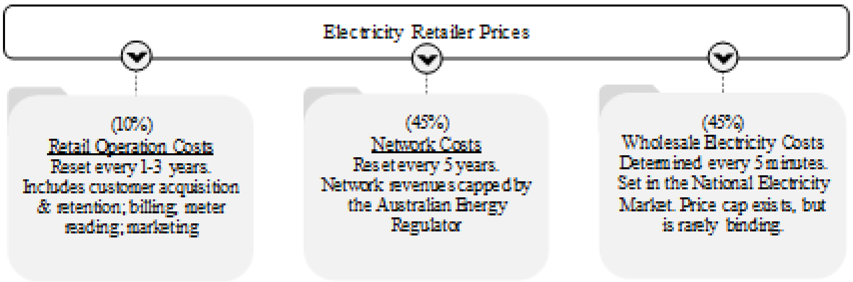


**Figure 7** Retail electricity prices [16].

Considering technological impacts, the conversion of learning curves to price rates is not consistently diminishing steadily with an increase in the number of units produced. Recent research efforts employ learning curve approaches to understanding electricity price mechanisms, emphasising the influence on the actual slope of the price through diverse factors. Corporate changes influence technology structures, reshaping market forces, emphasising the importance of price data over cost data, and reconstructing learning curves. This has implications for the usage of renewable energy at residential levels, drawing attention to the benefits and potential success of both fossil fuel and renewable energy approaches and their impact on reducing losses [17-19]. The rise in energy loss issues calls for a move beyond the demonstration phase supported by policy, pushing new solutions down into a learning curve.

Price setting in electricity remains a complex issue, presenting difficulties in determining efficient and appropriately regulated prices due to information gaps between market participants and regulators, as depicted in Figure 8. Consumption bundles, representing different consumer categories, help analyse price variations based on demand characteristics and peak/off-peak consumption proportions. The challenge lies in addressing "non-cost reflective prices", which distort signals, hindering market entry and consumer demand management. Criticisms of the current price-setting model emphasise a lack of clear objectives or conflicts within the existing objectives. Developing new operational strategies based on expected costs of renewable energy sources, such as storage batteries and solar panels, becomes critical for Australia's future energy mix [20]. Policymakers and energy generators face criticism for slow responses to the transition to a new energy mix and expanding away from fossil fuels. A carefully planned move is essential to avoid skewing the actual cost of a long-term sustainable energy supply towards less efficient energy schemes [21].

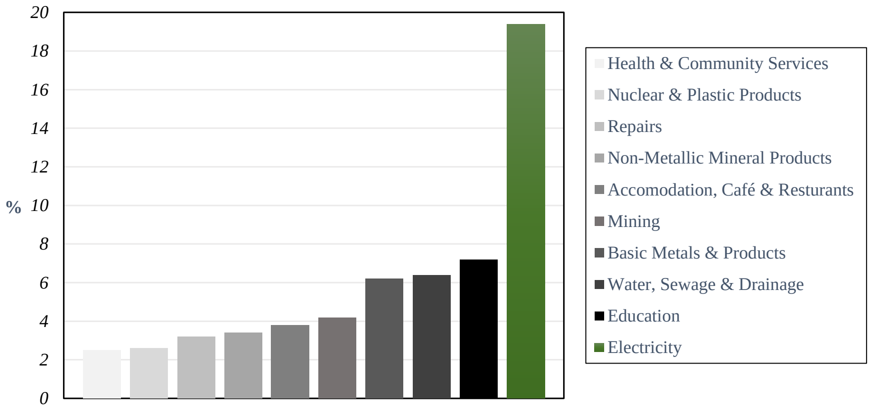


**Figure 8** Comparing electricity supply expenses with other industries [15].

## 5. Levelised Cost of Electricity

The Levelised Cost of Electricity (LCOE) framework, administered by the Commonwealth Science and Industrial Research Organisation [17, 18], is a pivotal tool for evaluating electricity costs. The Australian Energy Technology Assessment (AETA), conducted under the Bureau of Resources and Energy Economics (BREE), utilised this approach to project electricity costs for the year 2030, accounting for scenarios "with and without carbon price" [17]. The assessment encompassed forty electricity generation technologies, incorporating operations and maintenance (O&M) costs for solar and wind, projecting costs and operations up to 2050.

The LCOE formula is expressed as follows:

$$LCOE = KC + O\&M_{fix} + O\&M_{var} + FC + SC + PC \quad (1)$$

Where:

KC: Capital cost

$O\&M_{fix}$: The fixed cost of operation and maintenance

$O\&M_{var}$: The variable cost of operation and maintenance

FC: Fuel cost

L: Amortisation period

Cap: Capacity factor

SC: CO2 storage cost

PC: Permit cost when carbon price applies

r: Discount rate

IDC: Interest during construction

eff: The fuel conversion efficiency

emiss: The fuel factor

carbprice: The carbon price

The elements of the formula are defined by various sub-formulas:

$$KC = KC\ (\$/KW) \times \frac{r(1+r)^L}{(1+r)^{L-1}} \times \frac{1000}{cap\ \times 8760} + IDC \tag{2}$$

$$O\&M_{fix} = O\&M_{fix}\ (\$/\ MW_{yr}) \times \frac{r(1+r)^L}{(1+r)^{L-1}} \times \frac{1}{cap\ \times 8760} \tag{3}$$

$$FC = FC\ (\$/GJ) \times 3.6 \div eff \tag{4}$$

$$PC = emiss \div eff \div 1000 \times 3.6 \times carbprice \tag{5}$$

Figure 9 highlights significant findings for 2030, emphasising that wind technology emerges as the lowest-cost option. Carbon prices significantly impact black and brown coal costs. Carbon capture and storage technology (CCS) registers the highest LCOE, either with or without carbon pricing. Wind and solar are lower-cost technologies compared to fossil fuels, with solar costs decreasing by 15% $/MWh due to capital cost reductions. Network costs play a critical role in the overall structure of electricity bills across territories in Australia, emphasising the reliance on transmission and distribution systems [3].

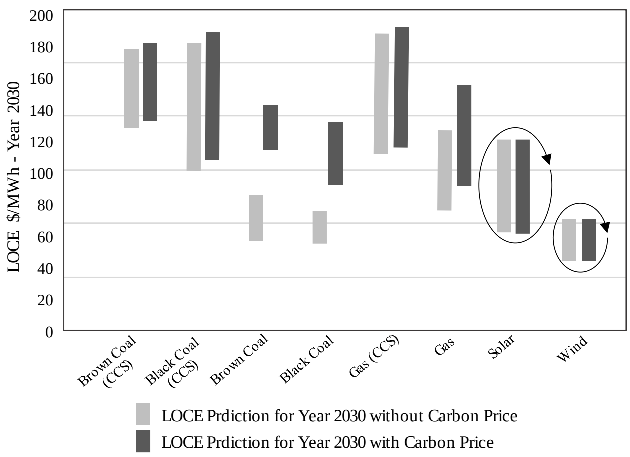


**Figure 9** Levelised cost of electricity with & without carbon price to the year 2030 [18].

Figure 10 outlines the expected costs of electricity bills, highlighting the distribution of costs across categories like green costs, carbon costs, retail costs, energy costs, and network costs. Network costs, associated with delivering electricity from generation sources to end-users through transmission and distribution networks, hold substantial weight in the pricing dynamics [22].

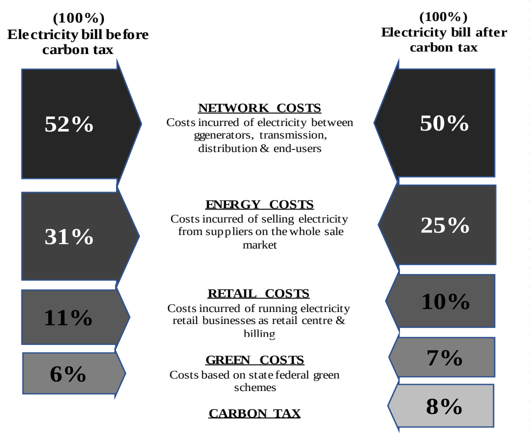


**Figure 10** Expected costs of electricity bills [22].

Lastly, Figure 11 illustrates the variability in electricity prices across different states in Australia, showcasing the dissimilarity influenced by factors like weather, population, and resource distribution among domestic suppliers within the same state [21, 23, 24].

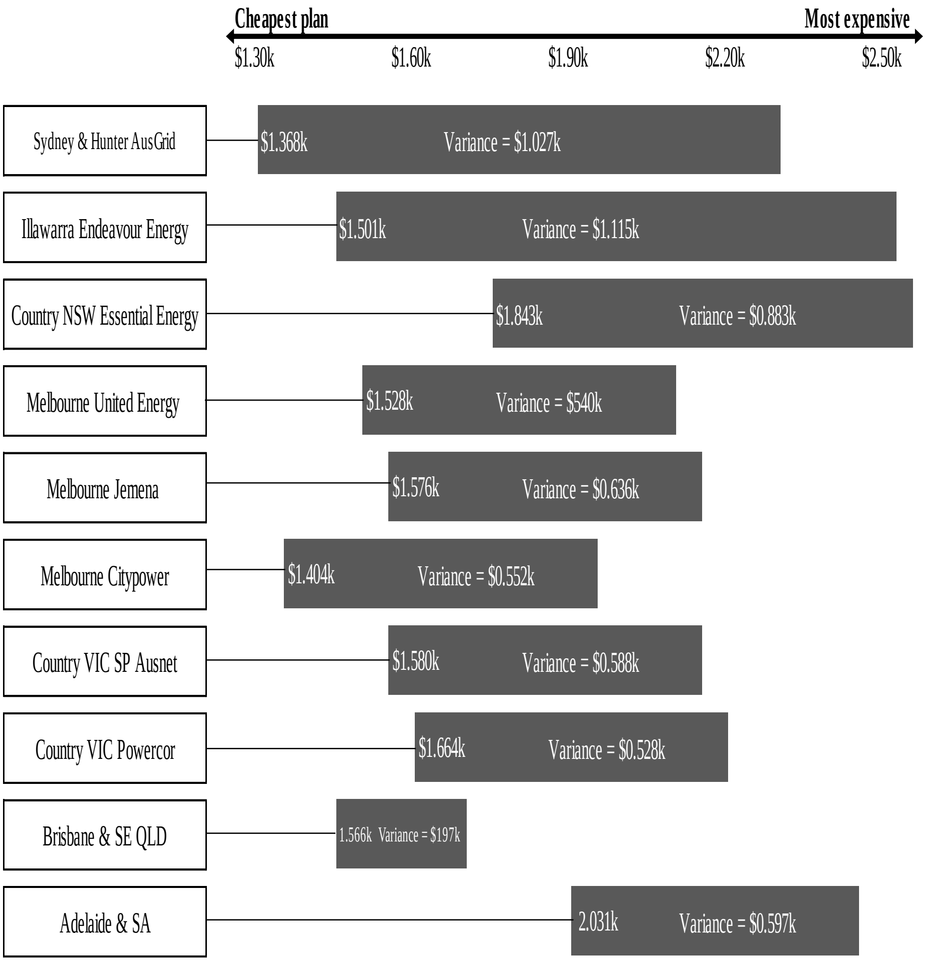


**Figure 11** Suppliers' pricing of electricity in Australia in the same states [25, 26].

## 6. Methods

In this study, methods were employed to analyse electricity demand data sourced from the Australian Energy Market Operator (AEMO). The process adhered to the guidelines outlined in [1] and [2], utilising Python programming language to establish a data frame for subsequent analysis. Confidence levels of 99% and 1%, along with confidence intervals, were employed, forming a robust foundation for further exploration [1, 2]. Pearson's correlation coefficient (PCC) played a pivotal role in unveiling the relationships among variables. Employing PCC allowed for the identification of highly positive and negative correlations, providing insights into the unity of demand events, potentially influencing peak and off-peak patterns and contributing to energy loss [2]. The statistical robustness of PCC, ranging from perfect negative (-1) to perfect positive (+1), portrayed an accurate representation of data clustering performance.

An additional step involved analytical resampling, utilising a nonparametric statistical inference method on the PCC results. This strategic approach aimed to retain highly associated demand variables, ultimately yielding less than 70 random samples for subsequent Energy Value Management (EVM) analysis [27-32]. The foundational plan was established by defining daily electricity demand for each end-user, encapsulating timely demand objectives (kWh) and corresponding budgets ($). These objectives were aligned with specific scopes, intending to meet approved total budget constraints for the entire day. The cyclic budget assumption postulated a consistent daily consumption pattern based on the benchmark measurements of Earned Value (EV), as defined in the provided formulas.

Energy Value Management (EVM) was executed through a three-tiered approach, accommodating the complexities of supply and demand logistics extracted from [1, 2, 4]. The initial phase involved identifying individual demand scopes, breaking down desirable demand limits into miniature plans across forty-eight half-hour intervals daily. This delineation established the scope baseline, measuring kWh units against costs incurred and generated from energy loss.

## 7. *EVM* Modelling

The *Earned Value Method (EVM)* aims to compute the influence of energy loss-driven cost based on desirable and undesirable demands. *EVM* is restricted to defining series distortion of the scope, cost and schedule performance of end-users' demand in a time-phased budget in plotted curves caused by energy loss. The baseline schedule defines interval start and finish times for each demand activity used by each end-user every half an hour forty-eight times a day, denoted between $t_1$ and $t_{48}$. Three aggregated parameters of *Planned Value (PV)*, *Earned Value (EV)* and *Actual Cost (AC)* against three demand ranges of average *(AV)*, peak *(P)* and off-peak *(OP)* are used to measure the influence of energy loss driven cost based on end-users' performance. Generally, *EV* provides a continuous picture of where individual users' electricity demand stands versus where it should have been as planned. In similar words, *EV* measures the level of demand supplied by generators against *PV* enquired by end-users; simply, it is the interval time demand of each end-user to cover their timely energy needs. However, end-users assume this fact is not obtained from the attributes or characteristics of delivering the electricity itself but from the service of the coverage the consumption of end-users' demand. Therefore, there is substantial differentiation between *PV* and *EV*. At the same time, *PV* is affected by the energy consumption behaviour-oriented paradigm of individual users' dimensions. Ideally, *PV* relies on a single interval decision of end-user demand system driven by passive attitudes that vary and affect different spatiotemporal levels. These individual demand metrics easily identify deviations from the *PV* values and the incremental progress from the expected baseline schedule. Thus, in simple words *EV* is the electricity supply delivered to cover end-users demand *(PV)*. In the eyes of end-users, the expectations of *EV* must have two options: zero when the power of the end-user is purposely switched off (see Figure 12a), or intermittent, which out of end-users control (see Figure 12b), or equal to *PV* when one-self demand is covered (See Figures 12c-e). All other demand scenarios in Figures 12f-o are not related to the passive demand attitude of end-users $PV \neq EV$, thus, do not satisfy the end-users need. Exclusively, the motives and drivers of energy demand made by energy consumers' can be primarily simplified via binary notations. Either $PV \approx EV$, that electricity demand being utilised and available to guarantee service levels, or $EV = 0$ when it is not. This assumption is because the willingness and the common objective of electricity consumption for end-users deny other influences caused by other consumption patterns. Such as those patterns driven by invisible environmental and technical consequences of demand practices that end-users deny, cause, or at least be part of. With the ubiquitous end-users demand in household energy-related settings, it is one case that makes the initial plan of *PV* unrealistic in the eyes of end-users and unequal to *EV* when the grid performance goes not deliver electricity. These realistic insights were considered for computing the set of time series data for analysis, where fifteen scenarios of demands are expected to be exhibited in the following Figures marked between Figure 12a and Figure 12o simultaneously.

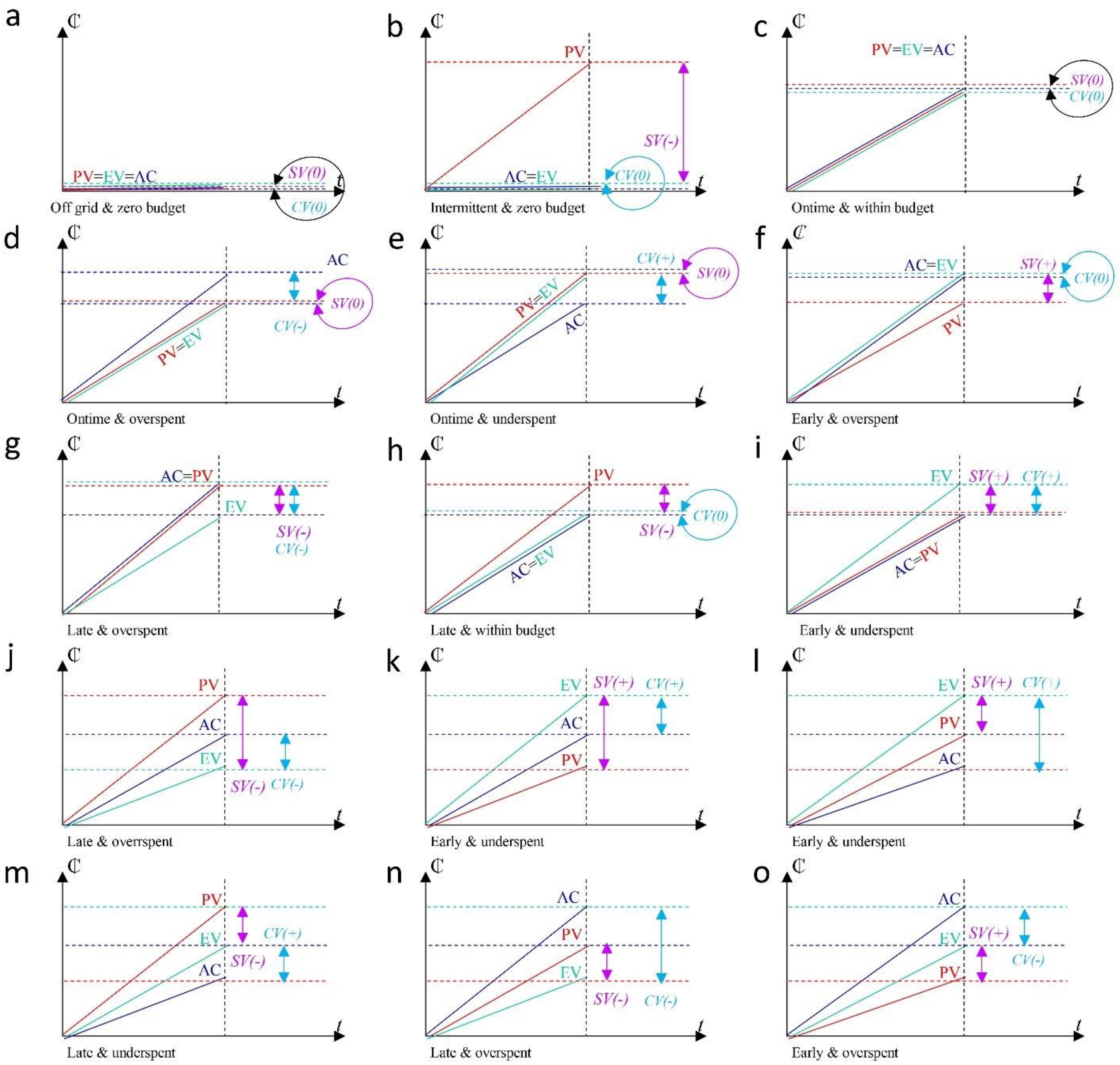


**Figure 12** Fifteen demand scenarios and their indicator changes for EV. a): Off grid & zero budget; b): Intermittent & zero budget; c): Ontime & within budget; d): Ontime & overspent; e): Ontime & underspent; f): Early & overspent; g): Late & overspent; h): Late & within budget; i): Early & underspent; j): Late & overspent; k): Early & underspent; l): Early & underspent; m): Late & underspent; n): Late & overspent; o): Early & overspent.

Supplementing to *PV* and *EV* roles and understanding, we are using *AC* to estimate the actual production cost per unit based on incurred power capacity costs in its generation. Simply put, the combined cost of load capacity factor from various plants such as *Coal plants*, *Open cycle gas turbine plants* and *Combined cycle gas turbine* combined with *ToU* is utilised to signify the monetary value of energy loss incurred in a particular time slot *($t_{n-1}$)*. The index of preliminary *PVs* has typically used the demand ranges of average *(AV)*, peak *(P),* and off-peak *(OP)* values of end-users' timely consumption referring to the schema of *Time of Use Tariff (ToU)*. The notions of *AV*, *P* and *OP* indicate three vectors of real life demands data. Thus, *AV*, *P* and *OP* are expressions of demand ranges based on activity durations denoted to $t_n$. The ranges of *AV*, *P* and *OP are* estimated based on the standard notation of the actual cost trading to the electric power generated by different sources of *CP*, *OCGT*, and *CCGT*. Based on this study objective, different results of end-users' demand predicted to be either one of Figures 12 b, c and f have *Scheduled variance* equal zero when *SV = EV – PV* Or when *EV = 0*.

The following analysis combines the smart grid's timely target, cost and schedule dimensions for the individual cyclic demand and then generates metrics for planning, control and measurement. The calculation of *EVM* requires to use of the following analytical formulas, which are also displayed in Figure 12:

$$Actual\ Cost\ AC\ =\ Actual\ Cost\ of\ Work\ Performed\ (ACWP) \tag{6}$$

$$Earned\ Value\ EV\ =\ Budgeted\ Cost\ of\ Work\ Performed\ (BCWP) \tag{7}$$

$$Planned\ Value\ PV\ =\ Budgeted\ Cost\ of\ Work\ Scheduled\ (BCWS) \tag{8}$$

$$Scheduled\ time\ =\ ST \tag{9}$$

$$Actual\ time\ =\ AT \tag{10}$$

$$Time\ Variance\ TV\ =\ ST\ -\ AT \tag{11}$$

$$Cost\ Variance\ CV =\ EV\ -\ AC \tag{12}$$

$$Scheduled\ variance\ SV\ =\ EV - PV \tag{13}$$

$$Schedule\ Performance\ Index\ SPI\ =\ EV/PV \tag{14}$$

$$Cost\ Performance\ Index\ CPI\ = EV/AC \tag{15}$$

$$Time\ Performance\ Index\ TPI\ = ST/AT \tag{16}$$

$$Cost\ Schedule\ Index\ CSI\ = EV/AC \times\ PV \tag{17}$$

$$Accumulation\ of\ the\ Project\ Budget\ at\ completion\ =\ BAC \tag{18}$$

$$Estimated\ at\ completion\ EAC\ =\ BAC\ /\ CPI \tag{19}$$

$$Variance\ at\ Completion\ VAC\ =\ BAC\ -\ EAC \tag{20}$$

$$\begin{gathered} To - Complete\ Performance\ Index\ (TCPI) = \\ Work\ Remaining\ (BAC - EV)\ /\ Funds\ (BAC - AC.) \end{gathered} \tag{21}$$

Based on the studies [1-3] the values 0.30–0.46 units denoted the range of desirable demand units. The time series data frame is divided into five observation points in time to trace the changing conditions of end-users incremental behaviours. The first *EVM* analysis assumes no operation circumstances are involved, and all data readings start from zeros; this step requires no simulation. The second, third, fourth and fifth observation points refer to *25%, 50%,75%* and *100%* of the demand progress on a daily bases and assume *CPI* variations at certain points where $t \in 1...48$, as $X_n$

*= {EV, PV, AC, CV, SV, CPI, SPI, TCPI, EV (t), PV (t), AC (t), CV(t), SV (t), CPI(t), SPI(t), TCPI(t)}*. Subsequently, the observations of the preliminary vector of all time series data made up to the point $t$ denoted to $X_{1\ldots48}$ and the vector of all end-users' observations of time series data denoted to $X = X_{1\ldots68}$ to estimate the changes occur in accordance with the influence of energy loss. In order to illustrate energy loss-driven cost, we defined the highest and lowest actual costs $AC_{High}$ and $AC_{Low}$ concerning overspent values (See Table 1). Figure 13 illustrates 25% of data results between $t_1$ and $t_{12}$ constitute the values of $AC_{High} = 490.27$ *unit* and $AC_{Low} = 419.54$ *unit* while $PV = EV = 397.32$ *unit*. Accordingly, the highest variance $VAR_{High} = CV_{High} = AC_{High} - EV = 56.83$ *unit* while the lowest variance $VAR_{Low} = CV_{Low} = AC_{Low} - EV = 419.54 - 397.32 = -13.90$ *unit* and driven by energy loss.

**Table 1** *EVM* Simulation Results.

| | | | *Cumulative Parameters* | | | | | | *None Cumulative Parameters* | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***t*** | ***ToU Tariff*** | ***WAP*** | ***PV*** | $AC_{High}$ | $CV_{High}$ | $AC_{Low}$ | $CV_{Low}$ | ***EV*** | ***PV*** | $AC_{High}$ | $CV_{High}$ | $AC_{Low}$ | $CV_{Low}$ | ***EV*** |
| *00:00* | $OP \leq i < AV_{min}$ | | *0.00* | *0.00* | *0.00* | *0.00* | *0.00* | *0.00* | *0.00* | *0.00* | *0.00* | *0.00* | *0.00* | *0.00* |
| *00:30* | $OP \leq i < AV_{min}$ | | *36.12* | *47.75* | *11.63* | *31.58* | *-4.54* | *36.12* | *36.12* | *47.75* | *11.63* | *31.58* | *-4.54* | *36.12* |
| *01:00* | $OP \leq i < AV_{min}$ | | *72.24* | *96.25* | *24.01* | *64.11* | *-8.13* | *72.24* | *36.12* | *48.50* | *12.38* | *32.52* | *-3.60* | *36.12* |
| *01:30* | $OP \leq i < AV_{min}$ | | *108.36* | *143.29* | *34.93* | *97.75* | *-10.61* | *108.36* | *36.12* | *47.04* | *10.92* | *32.84* | *-3.28* | *36.12* |
| *02:00* | $OP \leq i < AV_{min}$ | | *144.48* | *186.52* | *42.04* | *132.59* | *-11.89* | *144.48* | *36.12* | *43.23* | *7.11* | *32.47* | *-3.65* | *36.12* |
| *02:30* | $OP \leq i < AV_{min}$ | | *180.60* | *212.11* | *31.51* | *169.01* | *-11.59* | *180.60* | *36.12* | *39.81* | *3.69* | *25.58* | *-10.54* | *36.12* |
| *03:00* | $OP \leq i < AV_{min}$ | | *216.72* | *265.11* | *48.39* | *203.87* | *-12.85* | *216.72* | *36.12* | *53.00* | *16.88* | *32.78* | *-3.34* | *36.12* |
| *03:30* | $OP \leq i < AV_{min}$ | | *252.84* | *303.59* | *50.75* | *239.77* | *-13.07* | *252.84* | *36.12* | *39.45* | *3.33* | *33.99* | *-2.13* | *36.12* |
| *04:00* | $OP \leq i < AV_{min}$ | | *288.96* | *339.45* | *50.49* | *275.65* | *-13.31* | *288.96* | *36.12* | *39.01* | *2.89* | *34.00* | *-2.12* | *36.12* |
| *04:30* | $OP \leq i < AV_{min}$ | | *325.08* | *376.44* | *51.36* | *311.64* | *-13.44* | *325.08* | *36.12* | *39.91* | *3.79* | *33.79* | *-2.33* | *36.12* |
| *05:00* | $OP \leq i < AV_{min}$ | | *361.20* | *413.43* | *52.23* | *347.58* | *-13.62* | *361.20* | *36.12* | *39.65* | *3.53* | *33.49* | *-2.63* | *36.12* |
| *05:30* | $OP \leq i < AV_{min}$ | | *397.32* | *449.35* | *52.03* | *383.68* | *-13.64* | *397.32* | *36.12* | *40.15* | *4.03* | *33.67* | *-2.45* | *36.12* |
| *06:00* | $OP \leq i < AV_{min}$ | ***25%*** | *433.44* | *490.27* | *56.83* | *419.54* | *-13.90* | *433.44* | *36.12* | *40.92* | *4.80* | *32.34* | *-3.78* | *36.12* |
| *06:30* | $OP \leq i < AV_{min}$ | | *469.56* | *534.53* | *64.97* | *455.51* | *-14.05* | *469.56* | *36.12* | *44.26* | *8.14* | *32.57* | *-3.55* | *36.12* |
| *07:00* | $AV_{max} < i \leq P$ | | *497.33* | *575.78* | *78.45* | *491.41* | *-5.92* | *497.33* | *27.77* | *41.24* | *13.47* | *31.98* | *4.21* | *27.77* |
| *07:30* | $AV_{max} < i \leq P$ | | *525.10* | *613.29* | *88.19* | *527.10* | *2.00* | *525.10* | *27.77* | *40.97* | *13.20* | *31.87* | *4.10* | *27.77* |
| *08:00* | $AV_{max} < i \leq P$ | | *552.87* | *652.22* | *99.35* | *562.17* | *9.30* | *552.87* | *27.77* | *41.76* | *13.99* | *31.54* | *3.77* | *27.77* |
| *08:30* | $AV_{max} < i \leq P$ | | *580.64* | *690.57* | *109.93* | *596.88* | *16.24* | *580.64* | *27.77* | *42.50* | *14.73* | *30.64* | *2.87* | *27.77* |
| *09:00* | $AV_{max} < i \leq P$ | | *608.41* | *729.13* | *120.72* | *631.37* | *22.96* | *608.41* | *27.77* | *44.40* | *16.63* | *31.80* | *4.03* | *27.77* |
| *09:30* | $AV_{min} \leq i \leq$ | | *637.17* | *766.42* | *129.25* | *666.04* | *28.87* | *637.17* | *28.76* | *39.11* | *10.35* | *33.05* | *4.29* | *28.76* |
| *10:00* | $AV_{min} \leq i \leq$ | | *665.93* | *803.00* | *137.07* | *700.35* | *34.42* | *665.93* | *28.76* | *39.09* | *10.33* | *32.83* | *4.07* | *28.76* |
| *10:30* | $AV_{min} \leq i \leq$ | | *694.69* | *839.36* | *144.67* | *735.02* | *40.33* | *694.69* | *28.76* | *41.30* | *12.54* | *33.13* | *4.37* | *28.76* |
| *11:00* | $AV_{min} \leq i \leq$ | | *723.45* | *876.54* | *153.09* | *770.04* | *46.59* | *723.45* | *28.76* | *40.50* | *11.74* | *33.19* | *4.43* | *28.76* |
| *11:30* | $AV_{min} \leq i \leq$ | | *752.21* | *913.43* | *161.22* | *804.91* | *52.70* | *752.21* | *28.76* | *40.43* | *11.67* | *32.74* | *3.98* | *28.76* |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 12:00 | $AV_{min} \leq i \leq$ | **50%** | 780.97 | 950.63 | 169.66 | 839.23 | 58.26 | 780.97 | 28.76 | 40.71 | 11.95 | 31.48 | 2.72 | 28.76 |
| 12:30 | $AV_{min} \leq i \leq$ | | 809.73 | 988.14 | 178.41 | 872.66 | 62.93 | 809.73 | 28.76 | 39.96 | 11.20 | 30.84 | 2.08 | 28.76 |
| 13:00 | $AV_{min} \leq i \leq$ | | 838.49 | 1025.65 | 187.16 | 906.14 | 67.65 | 838.49 | 28.76 | 40.00 | 11.24 | 30.83 | 2.07 | 28.76 |
| 13:30 | $AV_{min} \leq i \leq$ | | 867.25 | 1062.97 | 195.72 | 940.12 | 72.87 | 867.25 | 28.76 | 39.22 | 10.46 | 30.81 | 2.05 | 28.76 |
| 14:00 | $AV_{min} \leq i \leq$ | | 896.01 | 1100.34 | 204.33 | 974.78 | 78.77 | 896.01 | 28.76 | 40.01 | 11..25 | 31.22 | 2.46 | 28.76 |
| 14:30 | $AV_{min} \leq i \leq$ | | 924.77 | 1137.97 | 213.20 | 1009.22 | 84.45 | 924.77 | 28.76 | 37.78 | 9.02 | 31.83 | 3.07 | 28.76 |
| 15:00 | $AV_{min} \leq i \leq$ | | 953.53 | 1175.31 | 221.78 | 1044.31 | 90.78 | 953.53 | 28.76 | 37.66 | 8.90 | 32.07 | 3.31 | 28.76 |
| 15:30 | $AV_{min} \leq i \leq$ | | 982.29 | 1212.59 | 230.30 | 1079.39 | 97.10 | 982.29 | 28.76 | 37.64 | 8.88 | 32.55 | 3.79 | 28.76 |
| 16:00 | $AV_{min} \leq i \leq$ | | 1011.05 | 1249.92 | 238.87 | 1114.46 | 103.41 | 1011.05 | 28.76 | 39.12 | 10.36 | 32.58 | 3.82 | 28.76 |
| 16:30 | $AV_{min} \leq i \leq$ | | 1039.81 | 1287.66 | 247.85 | 1148.95 | 109.14 | 1039.81 | 28.76 | 39.44 | 10.68 | 32.87 | 4.11 | 28.76 |
| 17:00 | $AV_{max} < i \leq P$ | | 1067.58 | 1326.03 | 258.45 | 1183.51 | 115.93 | 1067.58 | 27.77 | 40.67 | 12.90 | 32.35 | 4.58 | 27.77 |
| 17:30 | $AV_{max} < i \leq P$ | | 1095.35 | 1365.36 | 270.01 | 1217.13 | 121.78 | 1095.35 | 27.77 | 43.39 | 15.62 | 32.47 | 4.70 | 27.77 |
| 18:00 | $AV_{max} < i \leq P$ | **75%** | 1123.12 | 1406.00 | 282.88 | 1249.73 | 126.61 | 1123.12 | 27.77 | 47.98 | 20.21 | 32.60 | 4.83 | 27.77 |
| 18:30 | $AV_{max} < i \leq P$ | | 1150.89 | 1448.10 | 297.21 | 1281.67 | 130.78 | 1150.89 | 27.77 | 48.75 | 20.98 | 31.94 | 4.17 | 27.77 |
| 19:00 | $AV_{max} < i \leq P$ | | 1178.66 | 1489.74 | 311.08 | 1313.57 | 134.91 | 1178.66 | 27.77 | 48.40 | 20.63 | 31.51 | 3.74 | 27.77 |
| 19:30 | $AV_{max} < i \leq P$ | | 1206.43 | 1528.48 | 322.05 | 1344.82 | 138.39 | 1206.43 | 27.77 | 46.31 | 18.54 | 30.79 | 3.02 | 27.77 |
| 20:00 | $AV_{max} < i \leq P$ | | 1234.20 | 1565.25 | 331.05 | 1376.11 | 141.91 | 1234.20 | 27.77 | 43.42 | 15.65 | 30.20 | 2.43 | 27.77 |
| 20:30 | $OP \leq i < AV_{min}$ | | 1270.32 | 1601.03 | 330.71 | 1407.40 | 137.08 | 1270.32 | 36.12 | 43.53 | 7.41 | 29.26 | -6.86 | 36.12 |
| 21:00 | $OP \leq i < AV_{min}$ | | 1306.44 | 1636.20 | 329.76 | 1439.07 | 132.63 | 1306.44 | 36.12 | 44.07 | 7.95 | 29.68 | -6.44 | 36.12 |
| 21:30 | $OP \leq i < AV_{min}$ | | 1342.56 | 1671.04 | 328.48 | 1469.96 | 127.40 | 1342.56 | 36.12 | 44.64 | 8.52 | 30.25 | -5.87 | 36.12 |
| 22:00 | $OP \leq i < AV_{min}$ | | 1378.68 | 1704.29 | 325.61 | 1501.67 | 122.99 | 1378.68 | 36.12 | 44.85 | 8.73 | 30.22 | -5.90 | 36.12 |
| 22:30 | $OP \leq i < AV_{min}$ | | 1414.80 | 1737.81 | 323.01 | 1532.44 | 117.64 | 1414.80 | 36.12 | 44.18 | 8.06 | 30.09 | -6.03 | 36.12 |
| 23:00 | $OP \leq i < AV_{min}$ | | 1450.92 | 1774.34 | 323.42 | 1563.36 | 112.44 | 1450.92 | 36.12 | 41.08 | 4.96 | 30.92 | -5.20 | 36.12 |
| 23:30 | $OP \leq i < AV_{min}$ | | 1487.04 | 1812.74 | 325.70 | 1594.10 | 107.06 | 1487.04 | 36.12 | 40.15 | 4.03 | 30.74 | -5.38 | 36.12 |
| 00:00 | $OP \leq i < AV_{min}$ | **100%** | 1523.16 | 1858.71 | 335.55 | 1625.34 | 102.18 | 1523.16 | 36.12 | 45.98 | 9.86 | 31.24 | -4.88 | 36.12 |

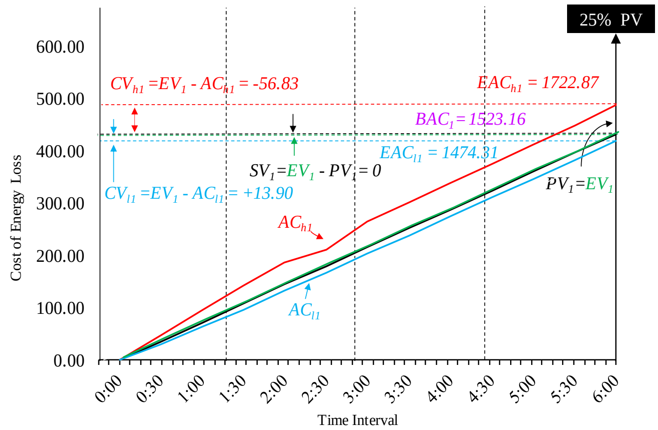


**Figure 13** *EVM* simulation of 25% demand.

Mimics of end-users demands have been generated from a set of *EVM* metrics to emulate several estimates of the activity cost within $t_n$ durations and for $X_n$ variables. *EVM* simulation in this study measures a volume of demand earned by end-users versus a volume of demand planned by suppliers that are expected to be earned as per the plan designed to avoid the phenomena of energy loss. The analysis was made to distinguish between four milestones to track the highest and lowest ranges of energy loss-driven cost based on the cyclic demand changes. Referring to the data of the simulation results in Table 1, simultaneously, Figure 13 displayed the analysis results after *25%* of the allocated time passed, particularly for the first six hours of demand during a day. The expectations of earlier analysis will lead to discovering the problem earlier and provide a better chance to fix it, although it is not the case with the electricity demand. The deviation between planned and actual costs has been defined based on EVM metrics. The results of low demand levels found $CV_{l1} = +13.90$ and $EAC_{l1} = 1474.31$ indicate no energy loss-driven cost occurs at the specified ranges. However, false probability signals were found within the ranges of maximum values where $CV_{h1} = -56.83$, and $EAC_{h1} = 1722.87$, evidence of several demands' overreactions occurred via demands cumulated. We can note that EAC is a linear extrapolation of current tendencies that could not influence corrective measures, deliver corrective actions to future risks, or confirm any assurance to rely on the system's current pattern. Instead, *EAC* helps indicate the potential cost problems based on the demand scale ranges to provide a warning signal and trigger the need for rectifying actions.

The second stage of demand progress shown in Figure 14 is the values of all individual demands computed on the same basis being done to the first milestone but for twelve hours of the day (50% of the daily demand load).

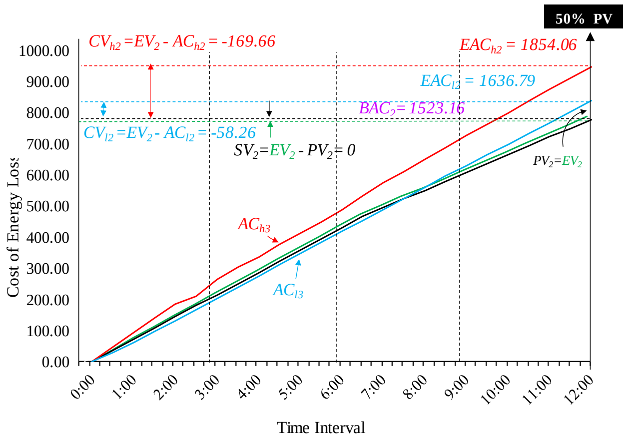


**Figure 14** *EVM* simulation of 50% demand.

After twelve hours of end-users demand, the line scatters in Figure 14 represent $CV_2$ and $EAC_2$, while the bar chart in Figure 15 illustrates the *CPI*. These new results indicate an increase in energy loss and cause more expensive demand than planned; this issue can also be distinguished through the increasing gap between $PV_2$, $EV_2$ and $AC_{H2}$, $AC_{L2}$.

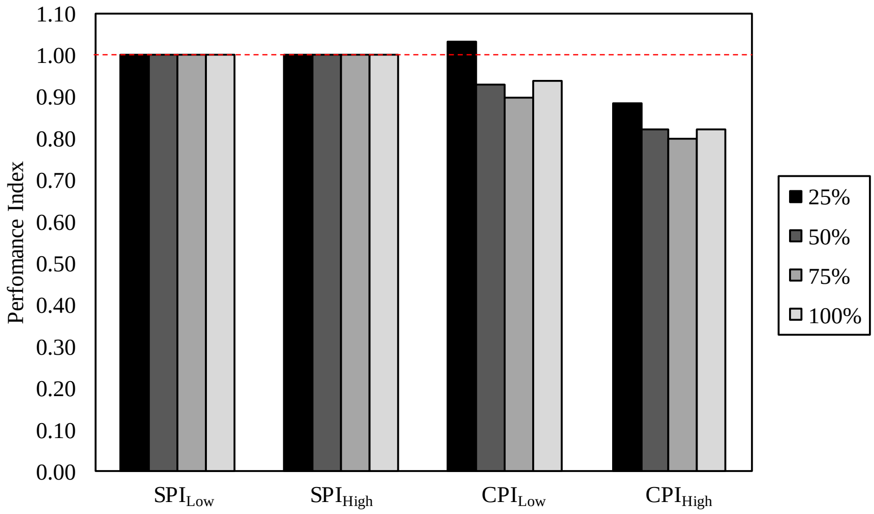


**Figure 15** CPI analysis.

Figure 16 and Figure 17 of the third and fourth stages of analysis mimic the measures of 75% of total demand (demand of eighteen hours a day) and 100% of total demand (twenty-four hours a day), subsequently capturing the scales of deviations. Figure 16 represents the cost overrun results of $CVh_3$ = -282.88, $CVl_3$ = -126.61, $EACh_3$ = *1906.8* and $EACl_3$ = *1694.87*. In this stage three, the tendencies of $EAC_{h3}$ and $EAC_{l3}$ display potential slippage of the cost overrun, likely providing a warning signal of continuously increasing the cost of energy loss as that can also be defined via $CVh_3$ and $CVl_3$. At a certain point in time, the S curve of EVM is often the most critical period, which at the earlier stages of the forecasts, requires reliable information on how to move up into the next stage. The variance tendencies found from the analysis patterns of $BAC_{1,2,3,4}$, $EAC_{l1,2,3,4}$, $EAC_{h1,2,3,4}$, $CV_{h1,2,3,4}$, $CV_{l1,2,3,4}$ are reliable indicators to show the variances of the past demand costs but unlikely to provide an accurate assumption of the future incurred costs, give room to consider other solution scenarios to assess the influence of energy loss.

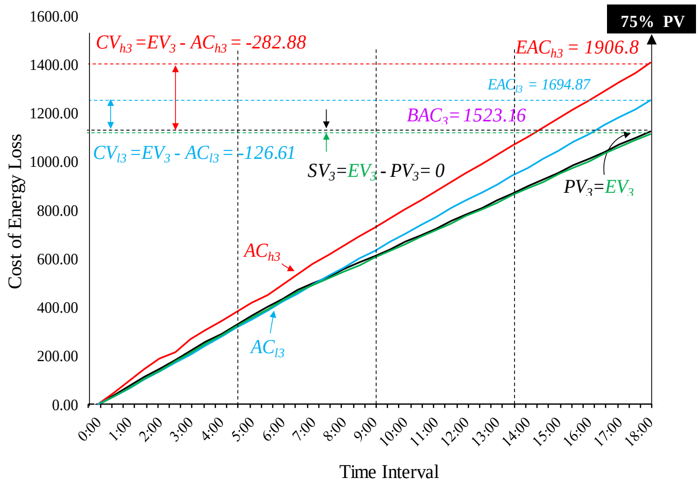


**Figure 16** *EVM* simulation of 75% demand.

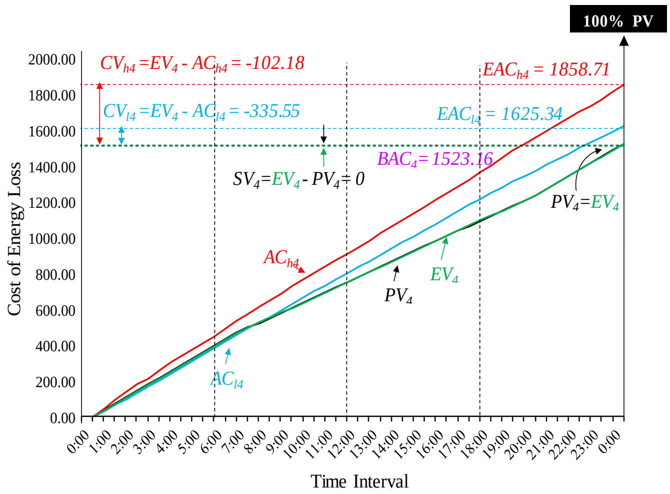


**Figure 17** *EVM* simulation of 100% demand.

Maximum demand:

$$(TCPI_{h1}) = (BAC_{h1} - EV_{h1}) / (BAC_{h1} - AC_{h1}) = 1.06 \tag{22}$$

$$(TCPI_{h2}) = (BAC_{h2} - EV_{h2}) / (BAC_{h2} - AC_{h2}) = 1.30 \tag{23}$$

$$(TCPI_{h3}) = (BAC_{h3} - EV_{h3}) / (BAC_{h3} - AC_{h3}) = 3.41 \tag{24}$$

Minimum demand:

$$(TCPI_{l1}) = (BAC_{l1} - EV_{l1}) / (BAC_{l1} - AC_{l1}) = 0.99 \tag{25}$$

$$(TCPI_{l2}) = (BAC_{l2} - EV_{l2}) / (BAC_{l2} - AC_{l2}) = 1.09 \tag{26}$$

$$(TCPI_{l3}) = (BAC_{l3} - EV_{l3}) / (BAC_{l3} - AC_{l3}) = 1.46 \tag{27}$$

So far, the *EVM* results found no chance for the end-users demand to complete its iterative cyclic demand on the proposed budget unless the cost performance index (TCPI) is improved, which computes the future required cost efficiency to fulfil a target *EAC*. *TCPI* is a comparative metric to indicate whether or not the estimate of *EAC* is realistic and reasonable. Given the *TPCI* of maximum demand (see formulas 22, 23 and 24) that found *TCPI >1* shows the cost of the demand exceeds the existing budget, which arises when energy loss increases. $TCPI_{h1}$ indicates that the performance needs to be raised at a cost efficiency of 106% from stage one to the end of the twenty-four hours demand. Likewise, the second and third stages of the analysis show $TCPI_{h2}$ = 130% and $TCPI_{h3}$ = 341% means higher margins of 0.30 and 2.41 require continuous increases to the performance at an efficiency cost, which is overly pessimistic. With minimum demand levels (equations 25, 26 and 27) in the first quarter of $TCPI_l$ (25%), the target value is assumed to be reasonable within 99%. In comparison, the results of the second and third quarters did not meet the specified management goal where extra work performance is needed at cost efficiency of 109% and 146%. In order to make the analysis results of *TCPI* meaningful, we compare it with the demand *CPI* illustrated in Figure 18, which indicates the cost efficiency possibly achieved if TCPI is reasonable. $CPI_{Low}$ results are *1.033, 0.93, 0.89 and 0.94,* while *CPIHigh* results are *0.88, 0.82, 0.79 and 0.81,* and have asymmetrical distribution among the four tested quarters to demonstrate that the values occur at varying frequencies.

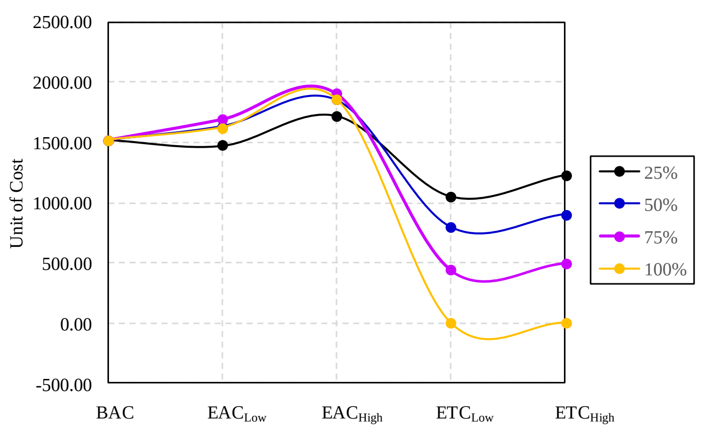


**Figure 18** Variations of BAC, EAC, ETC.

In Figure 18, the markers in the smooth lines scatter speak in favour of three measures: (1) *BAC* as a fixed amount and denoted to 1500 units; (2) *EAC* has a reasonable variation between 0.25% and 9.6%, particularly the gap increase between the second and fourth milestones; (3) *ETC*, where a slight slippage of unit averages found between high and low estimates for the four computed quarters, the estimated cost found decreases within a range of 55% and gradually toward the end of the iterative time-interval demand *($t_{1\ldots48}$)*. Figure 19 on the right-hand side, the lines and markers display the cost gap driven by energy loss denoted by upper black and dark grey lines and the gaps with the planned red demand line.

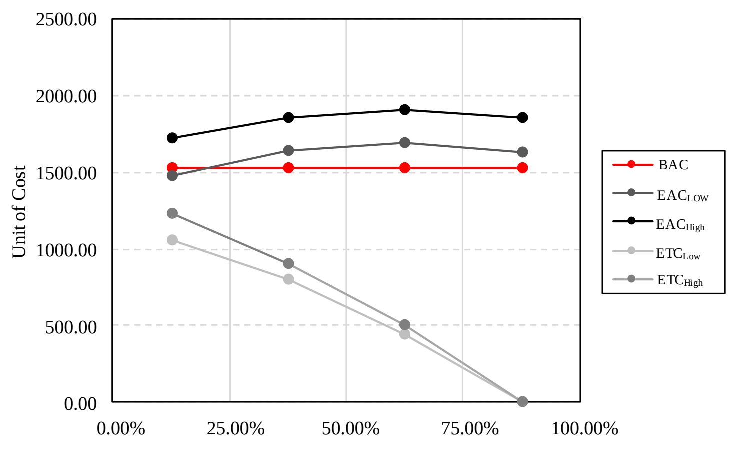


**Figure 19** Cost gap driven by energy loss.

From the analysis results of *EV, PV, AC, CV, SV, BAC, EAC, CPI, SPI, and TCPI* is worth mentioning that there are some significant challenges caused by energy loss implied in cost variances that should be overcome. As for cost, we can conclude that end-user demand causes disagreement in *CPI* values (See Figure 20). The inconsistency of *CPIs* alarming an anti-persistent issue, and the problem is more complex due to precedence relevance between multiple demand tasks. We can note that time management implied in the $SPI_{Low}$ *and* $SPI_{High}$ is not a concern because there is no intermittent issue of the power supply. And the energy demand was continuously flowing to cover end-users demand with no interruption counted or observed exclusively in the data used for this study. Another shortcoming of overrun cost driven by energy loss could be related to the demand system memory defined through the unreliable anti-persistent results, i.e., *EAC, CV, BAC*...etc., which may need further investigation in other future studies. And yet another drawback of critical tasks is the evidence of minimum and maximum risks proportional to the cumulated *AC* of energy cost against *EV* and *PV* (See Figure 20). It displays the influence ranges of actual cost driven from energy loss where the gap between *AC* and *EV* and *PV* speaks for itself that diverges from the planned demand target toward increasingly cost overrun. The illustrations in Table 1 and Figures 14-20 arouse a curiosity exhibited by *EVM* metrics to monitor *EVs* from the perspective of energy loss-driven cost via $AC_s$ analysis where the proposed end-users demand is equal to *EV = PV = BAC*. Per *Australian Electricity Market* plans, the preference of *PV* values to act within lower and higher demand ranges that the supplier prefers to achieve makes sense of the meaning of control where the spatiotemporal *EV* demand of end-users should match.

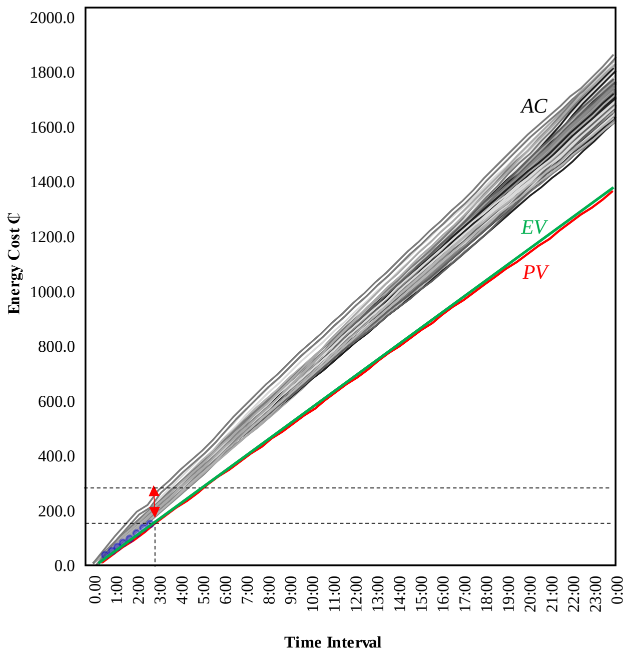


**Figure 20** AC, EV and PV of energy cost.

In Figure 21, the non-cumulative structures of the demand variables *($X_n$)* of end-users input space are displayed using *EVM* to derive control limits for multivariate independent variables. Figure 21 reveals the fluctuation range of non-cumulative levels of energy loss when not summed up to induce the individual effect. In this Figure, we can observe the timely extent of the energy loss issue by getting to the bottom where the individual demand behaviour of end-users. The variance at each point in the selected time interval is evident but during the first six hours and last four hours, the results were above and below the datum line of energy loss, showing some end-user behaviours could smoothen the loss curve plot that can be clarified via the following results of the cumulative curve.


**Figure 21** Non-cumulative energy loss.

Figure 22 shows the cumulative noise, and the patterns of independent demand variables denoted to the $CV_{high}$ (black curve) and $CV_{Low}$ (Purple curve). No real significant differences in anti-losses behaviours can be observed; in some limited occasions, a slight incline into lower than zero levels was observed within the first six hours of the day (12:00- 06:00 am), which makes sense as all the household demands slowdown during that period of time. The significant observation that the cumulative energy loss-driven cost consistently increases is denoted by the stripped gap between $CV_{Low}$ and $CV_{high}$.

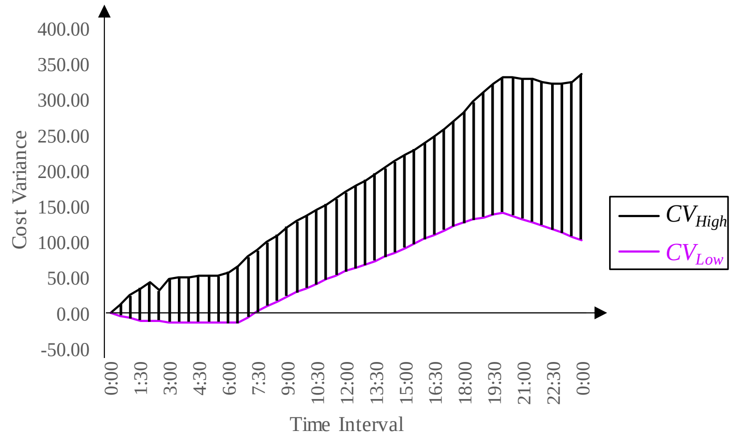


**Figure 22** Cumulative energy loss.

Figure 23 shows the vertical and horizontal measurements of the geometric distances among *PV, EV* and *AC* versus the cost and time scales. Our results highlight two aspects of energy loss-driven costs: (1) With distance from the preferred demand stripped area; the lowest demands of $AC_{Low}$ were found mostly within the preferred ranges (green line); (2) With distance from the preferred demand stripped area; the highest demands of $AC_{High}$ were found entirely out of the preferred ranges, resulting in more intensively occur of energy loss which also increase the risk factor (red line).

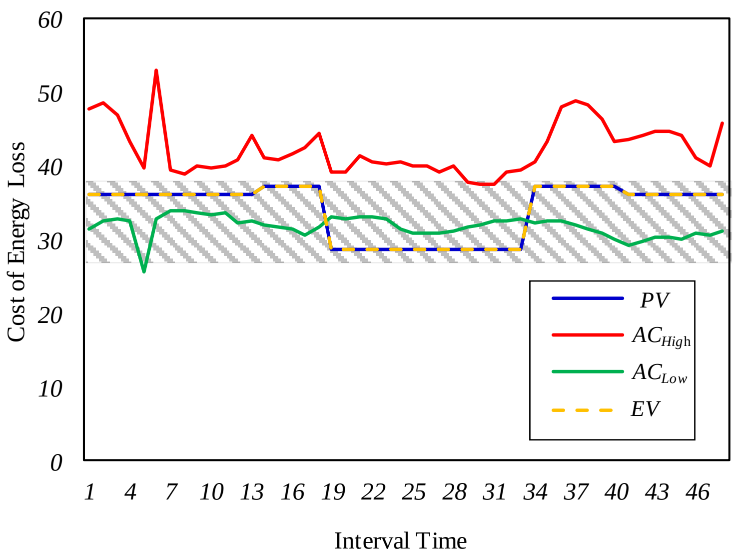


**Figure 23** Geometric distances between PV, EV and AC.

## 8. Conclusion

Complexity study has become popular in addressing system dynamics and framing networks. Yet, there is more to learn about linking simple events created by human behaviour, which leads to a complex end and influences organisations' outcomes. Mainly when focusing on subjective people in a complex system, such as residential end-users in electrical smart grid systems, such knowledge would be expected to have the greatest influence on developing a system. Perhaps understandably, end-users cause complexity and lie at the heart of the internal factors influencing and hovering around the electricity business performance by making an inconstant demand, affecting cost and price. The observations exhibit the extent of human behaviour as an example of non-linear dynamic behaviour in a complex system such as an electrical grid system. In particular, this study focuses on the spontaneous emergence of human actions to understand the consequences of events' scalability and the clustering dynamic of non-linearity. Despite the work done in this area, there is still a gap in the general conceptualisation of subjective human behaviours in electrical smart grid systems. A lack of integration of subjective end-user behaviours into accepted system operation models and a lack of agreement on facilitating a 'microgrid system' are obstacles to increase system efficiency.

An analytical model drew on the energy demand cultures' by using the *EVM* tool to support new strategies. Meaningful evidence of energy loss was found via the results of *EV, PV, AC, CV, SV, BAC, EAC, CPI, SPI*, and *TCPI*-defined venues that support the perception of optimising end-user behaviours and develops our understanding of human networks. As for the argument in this study, the problem is apparent confusion amongst end-users of electricity about what constitutes their demand "best interest". It is a businesslike matter with unfavourable consequences featured via the words "energy loss" to be aware of concerns raised with the end-users placement that affects electricity prices. We put energy loss under review to support the efforts of newly revised guidelines. It is hoped that the research will better support policymakers in taking on board the needed scope of restructuring, especially for the use of renewables in homes. In addition, this research would also support the reform approaches to new tariffs to mediate the relationship between all stakeholders and derive an equal advantage from the electricity utilities. This study further identified the key societal factors leading to losses and their significant relative costs by describing the pricing factors and estimating their magnitude and relative impact on energy loss with peak and off-peak demands, which is evident. This work helps fine-tune the *Electricity Market Rules* and regulates them based on consumers' diverse behaviours. It seemed to be our concern being valid that electricity cost and price are likely active when the electricity system is interconnected when the demand side of electricity is alive.

## Authors Contributions

Conceptualisation: A.Z.; Formal analysis: A.Z.; Investigation: A.Z., Y.A., M.E., N.A.; Methodology: A.Z., Y.A., M.E., N.A.; Project administration: A.Z., Y.A., M.E., N.A.; Resources: A.Z. Software: A.Z.; Validation: A.Z., Y.A., M.E., N.A.; Writing: A.Z.; Writing—review & editing: A.Z., Y.A., M.E., N.A.

## Agreement

This manuscript has been read and approved by all the authors.

## Funding

This research did not receive external funding.


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