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Two decades of progressive cost reduction: A paradigm shift for distributed solar photovoltaics and energy efficiency

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ABSTRACT

The increasing deployment of renewable energy resources has led to massive energy cost reductions worldwide in the past decade. The emergence of this cost revolution led electricity consumers to increasingly adopt distributed renewable energy resources to decrease dependence on traditional power grids. This paper applies the integrated resource planning framework, the objective of which is to design a least-cost electricity system by looking at renewable energy resources, efficient appliances, and demand response management strategies to reduce electricity bills. The results show that the commercial entity can save its electricity bill by $0.16 if it installs 6 MW solar PV over the lifetime of the solar PV plants. Besides, it was observed that wind turbines were not economically feasible to install at the site because of low wind resources. Biogas power plant is too expensive mainly because of the cost of fuel (waste). It also shows that by retrofitting 2000 compact fluorescent lamps (CFLs) with light-emitting diodes (LEDs), the company can save $0.15 million. By shifting between 0.5 MW and 1.4 MW of heating and cooling demand to periods of low tariff costs, the company can save $0.013 million annually. The climate transition plan for this company relies on PV, efficiency interventions and demand response. The study also demonstrates that an integrated resource planning framework can be used to plan a mini-grid.

1. Introduction

In response to the imperative to mitigate climate change and capitalise on cost-effective renewable energy sources, various companies, cities, and municipalities are transitioning to power systems predominantly reliant on renewable power generation. Through the adoption of renewable energy technologies for electricity generation, consumers can benefit from lower electricity bills. Additionally, in non-liberalised energy markets, many utilities employ the integrated resource planning (IRP) framework as a guiding principle in their decision-making process [1,2].

The IRP framework is a long-term electricity capacity expansion planning process that optimises the electricity system based on least-cost (LC) principles. It aims to identify the most cost-effective and efficient energy demand-side and supply-side technologies and forms a portfolio mix to meet future electrical demand reliably [3–6]. Non-liberalised energy markets, like South Africa and the Caribbean, predominantly rely on the IRP framework [7,8] to strategically plan their electricity systems.

In the ongoing energy transition, there is a growing trend of customers installing distributed energy resources on their rooftops or property sites worldwide [9]. Whether in small scale, utility customers, are transforming into utilities themselves and are referred to as prosumers. These customers actively produce and consume electricity rather than being solely passive off-takers of electricity generated upstream in the electricity network. This shift has led organisations to recognise the need for an integrated resource planning framework [10],

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Abbreviations

BAU	Business as usual
BW	Bid Window
CFLs	Compact fluorescent lamps
COUE	Cost of unserved energy
DSM	Demand side management
cTS	Current tariff structure
HVAC	Heating, ventilation, and air conditioning
IDM	Integrated demand management
IRP	Integrated resource planning
LC	Least cost
LED	Light-emitting diodes
LCOE	Levelized cost of electricity
MT	Medium term
NERSA	National energy regulator of South Africa
NPV	Net present value
PASA	Projected assessment of system adequacy
PV	Photovoltaic
RAF	Retirement annual factor
RE	Renewable energy
REIPPPP	Renewable Energy Independent Power Producer Procurement Programme
ST	Short term
UEC	Unit energy consumption
VoLL	Value of lost load
$\acute{\alpha}$	the scale parameter, determining how the failure rate changes through time
β	The shape parameter determining how the failure rate changes through time,
ρ	The air density
θ	The delay parameter – which provides for a delay before any failure occurs
v	The wind speeds from the mast
A	The rotor area
$f(x)$	Weibull probability density function
g	Generator
L_t	The number of hours in the dispatch period t
$P(x)$	Weibull cumulative distribution
P_{gmax}	Maximum generating capacity of generator g
P_w	The hourly power from the wind speed (w)
t	period
x	Age that is attached the operating period of the appliance
y	Year
$Cost_t$	The net present value of the system cost in period t
$BuildCost_g$	Built cost for generator g
$Demand_t$	Power demand in dispatch period t
$DF_{t\in y}$	Discount factor
$GenBuild_{g,y}$	The number of generating units built in year y for Generator g
$GenBuildUnits_{g,t}$	The number of generating units built in year y for Generator g
$GenLoad_{g,t}$	Dispatch level of generating unit g in period t
$FOMCharge_g$	Fixed operating and maintenance costs for generator g
$MaxUnitsBuilt_{g,y}$	The maximum number of units built in year y for generator g
$SRMC_g$	The marginal cost of generation g
$Units_g$	The existing number of units of generator g
USE_t	Unserved energy in dispatch period t
$LCOE_{tech}$	The levelized unit cost of producing electricity with a particular
NPV_{costs}	the net present value of costs
NPE_{tech}	net present value of energy produced or saved by an intervention
n	the number of years the technology will be in service
C_t	the capital cost
O_t	the operational cost
V_t	the variable cost
E_t	the energy produced or saved by an intervention

allowing them to comprehensively assess the technical implications and financial advantages associated with the chosen energy resources [11].

Extensive studies have been conducted on various technical, financial, and operational aspects of distributed energy generation and integration [12,13]. Some studies address issues and propose solutions for voltage control, power quality, and protection [14,15]. Adefarati et al. [16] evaluated the reliability and capacity of microgrid networks in handling distributed generation. Kasturi et al. [17] examined integrating photovoltaic (PV) systems and batteries within distribution networks, particularly emphasising voltage stability and energy loss. Meera and Hemamalini [18] optimised the distribution grid network to minimise power loss and voltage fluctuations using particle swarm optimisation. Mbungu et al. [19] demonstrated how demand response strategies can be coordinated and implemented within a microgrid environment. These studies evaluate the capacity of selected distribution networks or microgrid environments to accommodate the energy resources under investigation.

Among the studies on distributed energy generation, the second most prevalent type focuses on the economic dispatch and operation of integrated energy resources within microgrid environments [20–22]. These studies play a vital role in understanding how to economically dispatch renewable energy resources. However, in many dispatch studies, the capacity of the energy resources to be installed is pre-determined, and the least cost capacity is not determined. For instance, in Ref. [20], the demand response was assumed to operate for 4 h, implying that the operating strategy of the demand response is pre-determined. In contrast, researchers in Ref. [23] explored demand-side management but did not determine the least cost capacities for the PV and battery systems, focusing primarily on operations control.

The widespread investigations typically assume that the microgrid will install the capacity being studied, thereby excluding the determination of the least cost portfolio capacity mix [24,25]. In Ref. [25], the analyses focus solely on supply-side energy technologies. Additionally, the study assumes a reduction in load before considering supply-side interventions [25],. Consequently, future load/demand forecasts for installing energy efficiency measures [26,27] are adjusted. In Refs. [20–22,24], the operations analysis of demand response is incorporated, but it is not integrated into the capacity determination equations. This brings us back to the situation where capacities are pre-determined, as observed in the previous section [20–22].

As observed, there is a presumption that demand-side energy resources, particularly energy efficiency technologies, are inherently economic and automatically considered the least cost options for implementation. However, it is worth noting that the cost of renewable energy resources has significantly decreased over the past decade [1], hence making dual assessment of both supply and demand energy options a necessity. For instance, solar PV technology has experienced an 81 % reduction in unit electricity costs [28], while wind energy costs have decreased by 34 % [29]. In light of these significant cost reductions, a crucial question arises: Are demand-side energy resources still the initial least cost options when diversifying the energy portfolio? To address this question, this study conducts a planning case study focusing on a commercial entity in Gauteng Province in South Africa.

In South Africa, companies actively pursue energy diversification strategies to reduce their electricity bills and mitigate Carbon Tax payments. Diversification has become more accessible due to upcoming exemptions for power plants with generation capacities of up to 100 MW from generation license registrations [30]. In Gauteng, one specific entity has set a vision to diversify its energy portfolio. Fig. 1 illustrates the desired future outlook of this organisation. The entity must comprehensively understand available electricity energy resources and their associated costs to prioritise and evaluate the cost implications of different energy resources.

In this study, an IRP framework is utilised to analyse the technical operations of the microgrid, assess the financial implications, and determine the technology prioritisation required to reduce the electricity bill of the commercial entity under investigation. The organisation has experienced a consistent increase in its electricity bill since 2006, despite a decrease in electricity consumption during the same period, resulting in a total reduction of 5 GWh, as shown in Fig. 2. For ten years (2006–2017), the bill had surged by 400 %, equivalent to an average annual increase of $125 000. The continuous rise in municipal electricity tariffs guarantees further annual bill increases. In financial terms for 2017, the organisation paid $1.9 million annually for its electrical demand. With recent approvals by Eskom, the national utility, for revenue recoveries, tariffs are projected to increase by more than 15 % over the next three years, as reported by the National Energy Regulator of South Africa (NERSA).

A decade ago, investing in energy-efficient technologies was considered the best and most cost-effective strategy to address the escalating electricity bill, as supported by research [31–33]. However, the successful implementation of energy efficiency interventions is dependent on the presence of incentives. Energy audits are crucial in optimising energy consumption by providing insights into customers' consumption habits [34–36]. In 2008, Eskom, the National Utility, initiated an Integrated Demand Management (IDM) incentive program to financially compensate customers for electricity savings. This incentive program ended in 2015 when the South African government introduced the 12L incentive, allowing companies to claim financial benefits through the tax system [2]. However, the 12L incentive program was concluded by December 2022. As a result, both demand-side and supply-side energy technologies can now compete with demand-side interventions to reduce electricity bills without the impact of incentives.

The mentioned entity further carried out an energy audit to identify potential areas for energy efficiency interventions. Following the audit, a business case was formulated to evaluate the interventions based on their positive Net Present Value (NPV). However, in this specific case, the appraisal of energy efficiency interventions alone and solar PV alone

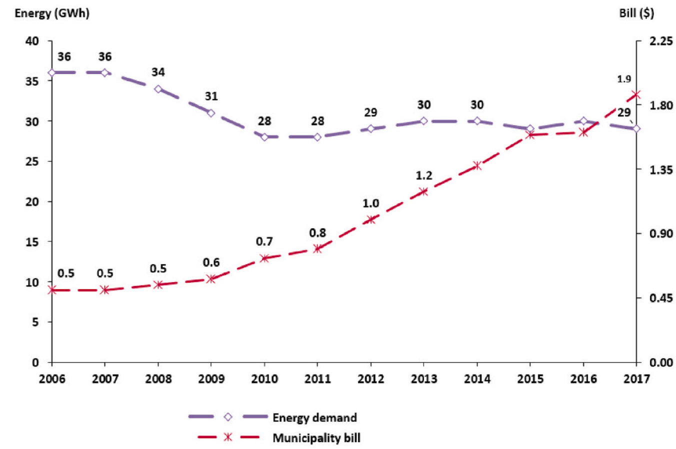

Fig. 2. The evolution of the organisation's bill from the municipality.

did not provide a conclusive decision, as the assessment for solar PV interventions also yielded positive NPV results. Moreover, these individualised analyses failed to present a comprehensive overview of the energy diversification plan that the organisation should pursue. This realisation prompted the recognition that a different energy initiatives/technology selection or planning approach was required.

The recent significant cost reductions in solar PV and wind technologies and the absence of policy incentives for energy efficiency raise the question of whether demand-side technologies, specifically energy efficiency technologies, are still the primary candidates for commercial customers aiming to reduce their electricity bills. To address this question, an integrated resource planning framework is employed to co-optimise both demand-side and supply-side technologies simultaneously for a business with time of use tariff. This planning framework offers a comprehensive perspective on the customer's electricity system plan by assessing the technical and financial implications of various options from both sides. It aims to determine the least cost (LC) capacity to install on the supply-side and demand side technologies to install to reduce electrical demand. Another crucial aspect this study considers is evaluating load/demand shifting to periods characterised by low tariff costs. The implication of the study is to demonstrate, with a case study, that capacity planning can be done in greater detail by taking the technological configurations into very fine detail. This was done using site-specific wind and solar resources and reviewing nearby waste

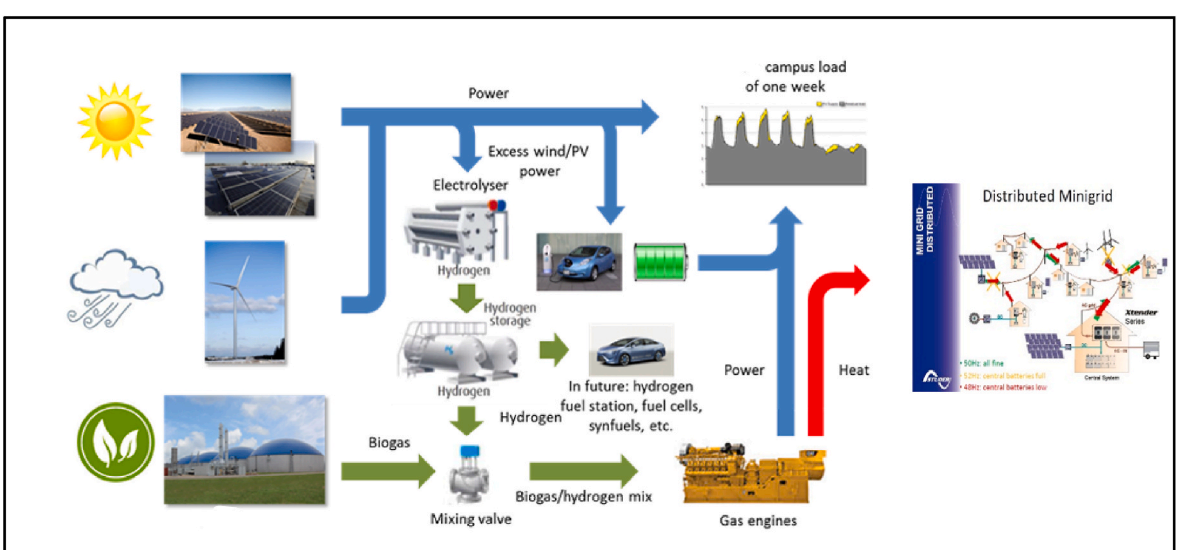

Fig. 1. Future desired outlook of the customer's campus outlook: the desired microgrid.

availability to feed biogas plants in order to assess the possible formation of a comprehensive renewable-based micro-grid. This study contributes to the existing literature in five significant ways.

- Utilise the integrated resource planning framework to optimise energy resource supply and demand technologies at the customer level, considering energy-efficient appliances and flexible load as co-optimisation candidates.
- Highlight the optimisation process that determines the capacity to be shifted solely based on price signals without pre-determining the capacity and operating cost periods of the shifted load. This enables dynamic and responsive load-shifting strategies.
- Showcase the integration of energy audit data into long-term power plans at the customer level, ensuring the inclusion of accurate consumption information in the planning process.
- Implement appliance stock modelling to forecast electricity demand plays a crucial role as an input within the integrated resource planning process.
- Demonstrate the usefulness of PLEXOS, a power system simulation and analysis tool, in determining operational schedules and assessing the financial implications associated with diversifying the energy mix of the organisation.

The paper is organised into six sections and is structured as follows: Section 2 presents the integrated resource planning methodological framework and its application at the customer level. Section 3 details data and input assumptions. The details include descriptions of scenarios, load, renewable energy resource profiles, and costs included in the planning framework. Section 4 details model calibration, validation and testing for reliability of the system. Section 5 presents the results and discusses the work. Finally, section 6 provides the conclusions and future improvements.

2. Methodological approach: applying an integrated resource planning framework at the customer level

2.1. Integrated resource planning framework

Fig. 3 illustrates both the supply and demand-side technologies considered in the plan as potential optimisation candidates, as guided by the vision outlook depicted in Fig. 1. The critical input assumptions are: demand forecast for the organisation, the tariff provided by the municipality and its forecast, the existing on-site power plants, their decommissioning schedule, as well as the costs and performance characteristics of new supply options. By utilising the integrated resource-planning framework, the organisation aims to determine the electricity plan with the least cost (LC), enabling the diversification of its electricity supply. The PLEXOS modelling tool has been employed in this study, and its applicability is further described in Sub-section 2.2.

2.2. PLEXOS modelling tool

The PLEXOS model is configured, built, and developed to optimise generation on hourly resolution throughout the year [18,37]. Additionally, the intermittent renewable energy resources – wind and solar PV and the load have hourly temporal resolution throughout the modelling period. PLEXOS is used internationally to model the energy markets, assess the profitability of purchasing power agreements (PPAs), and conduct integrated resource plans for countries [36,37], regions [7], and the world [38].

The PLEXOS model enables the co-optimisation of supply-side options, demand-side technology options, and new-build investment technology options throughout the planning horizon, aiming to achieve the least cost solution within predefined boundary conditions. PLEXOS utilises an objective function formulated as a mixed-integer problem, which minimises the NPV of the technologies to be constructed. The objective is to minimise retirement, construction, generation costs (fuel costs), and operating maintenance costs while ensuring that the capacity is adequate to meet current and future peak loads, along with a required reserve margin. The capacity optimisation in PLEXOS is governed by Eq. (1) and is subject to the conditions specified in Eqs. (2)–(4).

The modelling only considers the generation part of the electricity system, excluding the network constraints and new network investment costs. The outputs of interest are the total discounted system cost, the LC electricity capacity mix of electricity-generating and demand-reducing technologies to prioritise, the generation profile of supply-side technologies and the reduction profile for demand-side technologies. The study uses scenarios described in Sub-section 3.1 to create meaningful and well-defined future pathways.

$$\begin{aligned} Cost_T = & \sum_y \sum_g DF_y \times \left(BuildCost_g \times GenBuild_{g,y}\right) + \sum_y 1000 \times DF_y \\ & \times \left[FOMCharge_g \times P_{gmax} \times Units_g + \sum_{i \leq y} GenBuildUnits_{g,t})\right] \\ & + \sum_t DF_{t \in y} \times L_t \times \left[VoLL \times USE_t + \sum_g SRMC_g \times GenLoad_{g,t}\right] \end{aligned} \tag{1}$$

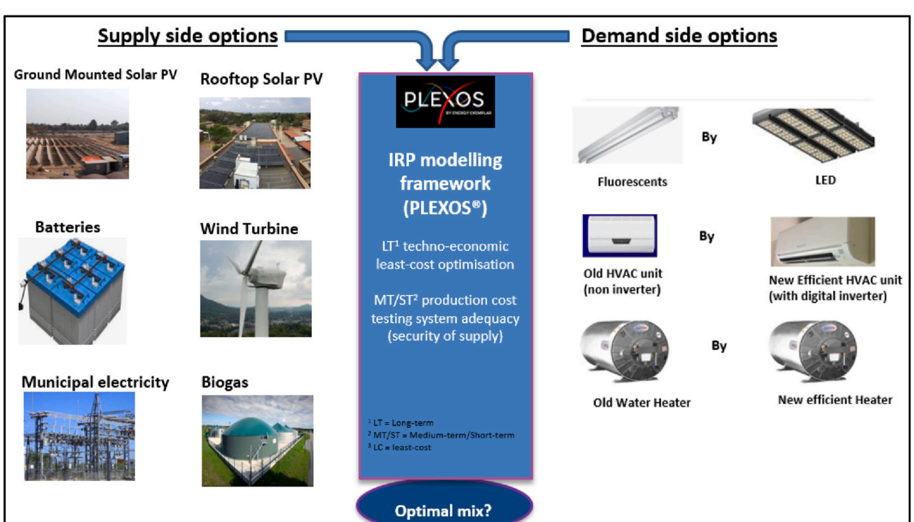

Fig. 3. Supply and demand technologies: candidates for techno-economic optimisation.

where $Cost_T$ is the net present value of the system cost in period t, DF_y is a function of DF, which stands for the discount factor within a year *y*, $FOMCharge_g$ is the fixed operating and maintenance costs for generator *g*, P_{gmax} is the maximum generating capacity of generator g, $Units_g$ is the existing number of units of generator g, $GenBuildUnits_{g,t}$ is the number of generating units built in year y for Generator g, L_t is the number of hours in the dispatch period *t*, VoLL is the value of lost load, USE_t represents Unserved energy in dispatch period *t*, $SRMC_g$ is the marginal cost of generation *g*, and $GenLoad_{g,t}$ is the dispatch level of generating unit *g* in period *t*.

Eq. (1) is subjected to three constraints, listed as follows.

1. Energy demand is met by satisfying Eq. (2)

$$\sum_{y} GenLoad_{g,y} + USE_t = Demand_{\,t} \tag{2}$$

2. Energy dispatch is feasible for all generators and all periods through Eq. (3):

$$\left(GenLoad_{g,t} \leq Pgmax \left(Units_g + \sum_{i \leq y} GenBuildUnits_{g,y} \right) \right. \tag{3}$$

3. Feasible Builds:

$$\left(\sum_{i \leq y} GenBuild_{g,i} \leq MaxUnitsBuilt_{g,y} \right) \tag{4}$$

with $Demand_{\,t}$ is the power demand in the dispatch period *t*, and $MaxUnitsBuilt_{g,y}$ is the maximum number of units built in year *y* for generator *g*.

Given its robust simulation, PLEXOS can handle 4 phases of simulations, each serving a different purpose. Eq. (1) solves the long-term plan (LT Plan phase) – which deals with the LC technology mix to install. LT Plan determines the LC capacity size (MW) of either supply or demand side technology (energy efficiency technology) to install. LT Plan also defines the timing of such new investments – which year are they economical to install. The second phase is the project assessment of the system (PASA) phase, which deals with system outage scheduling and reserve margin allocation. The schedule following PASA is the medium-term schedule (MT) – which explicitly deals with maintenance schedules and outages and optimises decisions spanning weeks, months, or years.

The last phase is the short-term (ST) schedule, which deals with chronological unit commitment, ramping requirements, and detailed economic dispatch profiles of the power system. ST phase optimises decisions for the short term (an hour or less). In addition, the ST phase highlights the economic dispatch of generation profiles for supply-side technologies and demand reduction profiles for demand-side technologies.

The organisation is tied to the municipality distribution grid. Therefore, the municipal grid meets its ramping requirements, allowing the size of demand response to be as large as the model economically determines. As a result, the model is not set for any ramping boundaries and needs as the grid is assumed to offer this microgrid (the organisation) unlimited flexibility [39].

The study runs the three optimisation schedules so that the customer knows. These are described as follows.

1) How to reduce electricity system costs in the long term through new investments, economic dispatch and shifting the shiftable loads to periods of low tariff costs,
2) the quantity of electricity demand to be reduced by installing efficient appliances, and
3) the amount of electricity demand that can participate in a demand response strategy. The paper does not give details of which load control strategy or demand response strategy to implement. Instead, the study highlights the maximum quantity of demand (MW) to shift to minimise system costs.

2.3. PLEXOS modelling environment

PLEXOS is an optimisation modelling environment whose fundamental structure is shown in Fig. 4. The optimisation takes place within the PLEXOS engine, receiving inputs from both the relational data base (plant's parameters) and text file (load profile and resource profiles). The relational database contains portfolio options and their performance characteristics. These performance characteristics are technical, economic and environmental in nature and are presented in Tables 1–3. These parameters are also featured within the optimisation equations shown in Equations (1)–(4), and their values per plant are shown in Appendix, Tables A.1 – Table A.5.

Carbon dioxide (CO_2) is often modelled as a function of generation for both municipal electricity grids (Tshwane grid) and biogas power plants, whereas SO_x (SO and SO_2 by-products) is best modelled as a function of fuel used. This model is only applicable to biogas plants that use fuel locally at the business site. NO_x (NO and NO_2) is often modelled using a combination of generation and fuel emission properties along with the scaling biogas plant emissions scalar factor.

3. Data and input calculations and assumptions

When conducting an integrated resource planning study, about six types of inputs are needed. These are.

1) Load/electrical demand forecast
2) Renewable energy resource profiles
3) Energy efficiency resource characterisation
4) Costs – capital investment costs, fuel costs, operating and maintenance costs

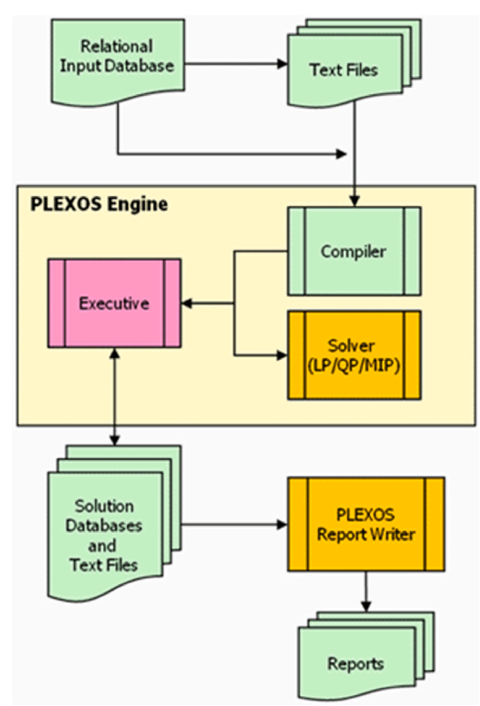

Fig. 4. Underlying PLEXOS operational environment [40].

Table 1
Technical parameters.

Parameters	PLEXOS Environment
Capacities	Used in both Long term (capacity determination), medium term (adequacy stability or flexibility assessment) & short term
Minimum stable generation	Minimum generation, below which point it becomes uneconomic to run like biogas plant at low capacity factors.
Maximum generation	Each generation have maximum capacity set.
Ramp rates	For diesel generators, 2 MW/min.
Heat rates	For biogas heat rates are important as they determine the efficiency of how the plant uses the fuel.
Minimum up and down times	The minimum generation level when the unit is committed Adds only one additional constraint per generator/period to the formulation. Generally easy for the solver to optimise, unless MSL is a very high proportion of capacity.
Failure/availability rates	5 % assumed failure rates for both solar \pv and wind
Maintenance rates and time	Assume % spent in maintenance by different plant types
Load forecast	The initial shape is given as a growth parameter. The shape does not change and is put into the model, as shown in Fig. 4, for a full year (base profile).
Resource generation profiles	For wind, solar and waste (as shown in Fig. 13(a) and Fig. 13(b)

Table 2
Economic parameters.

Parameters	PLEXOS Environment
Individual fuel costs,	Fuel costs as applied to biogas are described in Table A.5 in the Appendix.
Variable O&M rates	Variable costs for each plant type and the data assumption are shown in Table A.5 in Appendix.
Start costs,	Fuel costs as applied to biogas (See Table A.5 in the Appendix
Tariff cost profile	As shown in Fig. 16

Table 3
Environmental parameters.

Parameters	PLEXOS Environment
Pollution	Particulate emissions (sulphur dioxides & Nitrogen dioxides) from the municipal electricity (based on Eskom coal grid factors)
CO_2	Carbon dioxide as per Eskom grid emission factor
CH_4	Methane as per Eskom grid emission factor
N_2O	Nitrous Oxide as per Eskom grid emission factor

5) Tariff from the municipality
6) General assumptions such as the discount rate (the study assumes a 10 % discount rate)

This study employed scenarios to manage future uncertainty and test the impacts of drivers of change in the future. This section gives a detailed account of the inputs used in this study.

3.1. Scenario definitions and considerations

Since planning for the future is highly uncertain, the modelling tests three future possibilities through scenarios. It is implausible that one possible future will unfold. The scenarios provide a framework for exploring future energy perspectives, various combinations of technology options and their implications. One of these future possibilities is the business as usual (BAU) scenario that looks at the organisation's current energy system without considering further investments into new energy infrastructure. The second and third scenarios are the LC scenarios with demand-side management (DSM) (LC cTS) and LC without DSM (LC cTS (no DSM)). Table 4 presents the detailed assumptions for each of the scenarios.

Table 4
Detailed inputs in each scenario.

Scenario	Key Assumptions
Business as Usual	• The model optimally dispatches the existing organisation's capacity (1.9 MW of solar PV) and the municipality's imports to meet the expected electricity demand at the LC. •The organisation will not build any new supply-side energy options. •The municipality's tariff structure will remain the same throughout the planning period but will increase in absolute terms each year. •The existing fleet has been decommissioned as per the expected decommissioning dates.
LC with DSM	•The model freely optimises the energy mix based on the principles of the LC. •New supply options include wind, solar PV, biogas, and batteries (Li-ion). •New (renewable energy) RE supply options are limited to what the campus can accommodate spatially. The maximum installable capacity assumptions are as follows: o Max energy efficiency potential of 5.1 GWh in the form of lighting, heating ventilation and air conditioning (HVAC) and water heating oUp to 8.5 MW of additional Solar PV oUp to 2 MW Wind oUp to 2 MW Biogas •Wind and solar PV costs align with the organisation's procurements, reducing by 30 % and 25 % by 2030, respectively, aligning with international estimates. Battery costs starting at Draft IRP 2016 values with moderate learning (cost reduction of 66 %) assumption to 2030. •The existing organisation's fleet was decommissioned as per expected decommissioning dates. •Municipality tariff is assumed to increase as per IRP LC scenario from the organisation analysis [18] - no change to tariff structure. •Discount Rate = 10 % (Nominal) •Cost of Unserved Energy (COUE): Assume the National Energy Regulator of South Africa (NERSA) rate/kWh for the commercial sector: $7036/MWh
LC without DSM	•All the assumptions at the LC with demand-side management options •Energy Efficiency interventions and Demand response initiatives are not considered.

3.2. Electrical demand forecast

The critical input for IRP is the anticipated demand for the future. The optimised technology options meet this demand. Demand forecast requires several assumptions to get plausible future electricity demand. In this study, the organisation's demand was 30 GWh in 2017, with a peak demand of 7 MW. Fig. 5 shows the weekly demand profiles for Summer and Winter. In Summer, peak demand occurs in the afternoon when the need for cooling of offices increases. In winter, heating is required early in the day when it is cold. Hence, the Winter demand peaks in the mornings. The demand profile shapes for Winter and Summer are assumed to stay the same, as shown in Fig. 5, into the future before the implementation of any demand intervention.

Thus, the only change in demand will be when a demand intervention is implemented economically through model optimisation. Secondly, the analysis assumes that the organisation will not increase its workforce by around 2000 in the next ten years; hence, the demand is not expected to increase in the future. Finally, based on the HVAC replacement program that the organisation adopted in 2019, it is assumed that the demand will be on a declining trajectory.

The organisation adopted a replacement strategy for HVAC systems. Any HVAC unit needing replacing (due to retirement or failure) will be replaced with an efficient one. Therefore, the demand will decrease slightly over time as new HVAC units are installed, reducing unit energy consumption for HVAC systems. Most of the HVAC systems within the organisation are single-unit HVAC systems installed in offices. There are very few HVAC systems directly opposite most buildings in China [39]. Therefore, in the future modelled energy plan, demand forecasting is

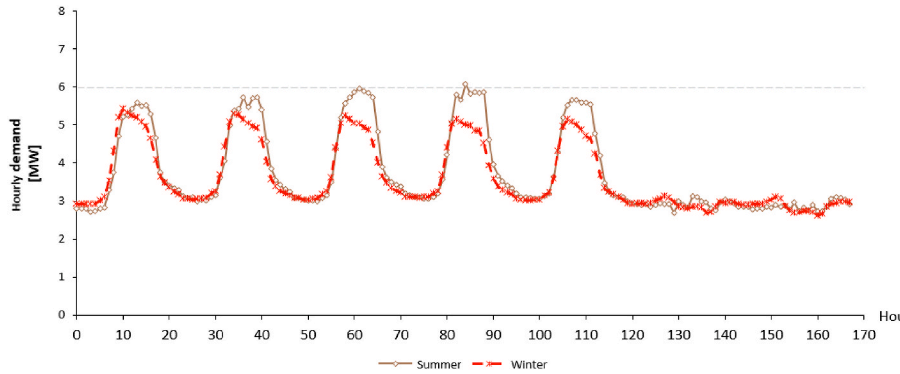

Fig. 5. Typical weekly load profile for both Summer and Winter.

considered as the HVAC replacement strategy detailed in Section 3.3.

3.3. The declining electrical demand forecasting: embedding HVAC stock modelling

A comprehensive dataset regarding the appliances employed within the organisation was available and obtained through an energy audit. Leveraging this extensive data, the study utilises appliance stock modelling to forecast future demand, specifically focusing on the HVAC replacement strategy outlined in Section 3.2. Additionally, in order to assess and evaluate the electrical demand implications resulting from these regular HVAC replacements, stock modelling was performed employing a Weibull survival function as described in Eq. (5). Weibull distribution was chosen over poison distribution survival function and others because it allows for more accurate predictions [41,42]he survival function in Fig. 6 was closely related to the longevity of HVAC appliances that the company analysed shared.

$$P(x) = e^{-\left(\frac{x-\theta}{\alpha}\right)^{\beta}} \tag{5}$$

The *P(x)* presents Weibull cumulative distribution, which is mainly used for modelling appliance reliability and decay, ultimately giving the probability that the appliance is still in use at age *x*. θ is the delay parameter – which provides for a delay before any failure occurs. β is the shape parameter determining how the failure rate changes through time, and $\acute{\alpha}$ is the scale parameter, determining how the failure rate changes through time. Weibull probability density function f(x) in Eq. (6) also uses the three parameters used in conjunction with Eq. (4)

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\theta}{\alpha}\right)^{\beta-1} e^{-\left(\frac{x-\theta}{\alpha}\right)^{\beta}} \tag{6}$$

Most appliances do not take up to their lifetime to fail. Therefore, the correct decay profile should be adjusted with at least a 5-year actual decay/replacements factor to get the proper Weibull distribution for appliances under consideration [18,43]. Unfortunately, there is no such data from this customer; thus, only theoretical coefficients are used. The initial values for $\beta = 3$, $\theta = 0.5$, $x = 1$ and $\alpha = 9.9$. These parameters are unknown for any stock that is estimated, and for estimating the survival of the HVAC in this study, available data about lifetime and replacements that had happened in the past 10 years was used to calibrate this survival function to match the actual data.

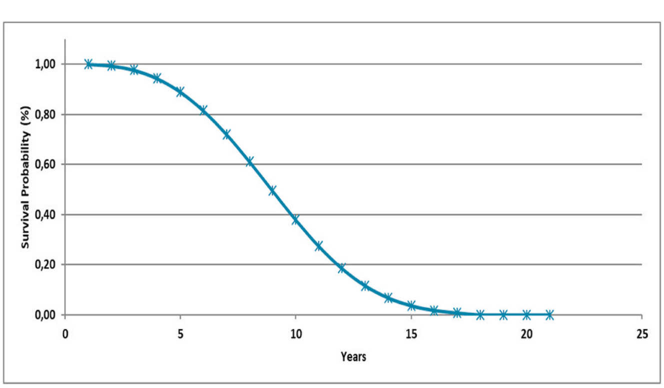

Fig. 6. Survival probability trajectory for HVAC units.

Eq. (6) presents the survival probability function used to project retiring stock, while Eq. (7) and Eq. (8) project sales and retirement.

$$Retirements\ (j) = \frac{Stock(j)}{L} \times RAF \times (1 - P(x)) \tag{7}$$

$$Sales\ (j) = Stock\ (j) - Stock\ (j-1) + Retirements(j) \tag{8}$$

where *j* is the year of the analysis, *L* represents the average lifetime of the appliance. This is the average length of time between the purchase of a new appliance and its removal from the operating stock. The removal can be through either failure, early replacement or scrapping. Retirements (*j*) is the total number of appliances that retire from the appliance stock during year *j. RAF* is the retirement adjustment factor and annual replacement factor used to calibrate the model to the observed HVAC retirement data received from the company's facility department. P*(x)* is the Weibull cumulative distribution factor derived from Eq. (5), *j* is the year, and *j*-1 is the period prior to the current year. Stock (*j*) is the total number of appliances bought by the company in the year (*j*) and are in service at the end of the year [44]. Purchases (j) are new appliances (HVAC units) bought by the company in the year (*j*).

The customer has about 2500 HVAC units of varying sizes. The number of HVAC systems will not increase or decrease; hence, there must be 2500 units every year. The survival function, as shown in Fig. 6, is multiplied by the number of units used to retire existing units. Eq. (8) is then used to derive new purchases each year and add them to the existing stock to keep the balance of the HVAC required in the system. As new efficient HVAC units replace old appliances, the average unit energy consumption improves. Since there was no information on the age of the existing appliances, all HVAC units were assumed to have the same survival trajectory as presented in Fig. 6. Given this survival trajectory, the HVAC units will retire and be replaced, as shown in Fig. 7. Every new colour represents the stock that was purchased in year *j. T*he colour shows how that stock follows the derived survival function in Fig. 6 until it is out of stock.

Based on the above assumptions, by 2030, 92 % of existing HVAC units will be replaced with new efficient ones, as shown in Fig. 7. The remaining 8 % will be out of the system by 2034. As a result of the replacement strategy employed and modelled, as shown in Fig. 7 and using the survival function, as shown in Fig. 6, the HVAC stock increases some energy efficiency gains. The efficiency gains of the stock are shown

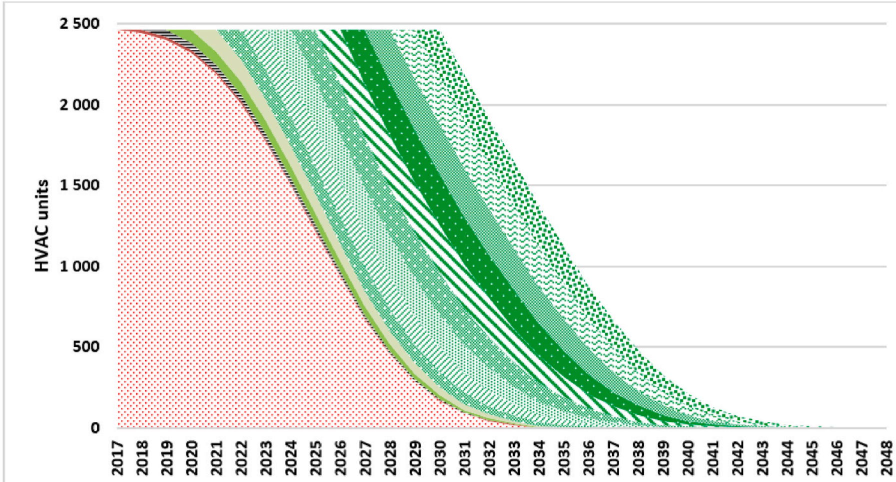

Fig. 7. Retirements of old HVAC units (red dots) and sales of new HVAC units. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

in the decreasing unit energy consumption (UEC) of HVAC stock over time. The base UEC was 2614 kWh per HVAC unit, and by 2030, it would improve to 2059 kWh per HVAC unit until it is ultimately 1890 kWh once all the old stock has been replaced with the most efficient units. Ultimately, the electrical energy consumption from HVAC units decreased from 6.44 GWh in 2017 to 4.91 GWh in 2030. Forecasting electricity demand in this manner accurately accounts for energy saved through the optimisation process and the energy saved due to the HVAC replacement strategy.

Accurately distinguishing energy savings derived from replacements versus those resulting from the model optimisation process prevents any double counting. Equation (8) computes the projected energy savings achieved through optimisation. Over the course of 15 years, the total annual electricity demand is projected to decrease by 6 % between 2017 and 2034, primarily due to the replacement of old HVAC units with new energy-efficient ones, refer to Figs. 8 and 9.

$$\textit{Optimised energy savings} = \textit{Load}_y - \textit{forecast load}_y \tag{9}$$

3.4. Energy efficiency technologies and demand response

The IRP planning framework co-optimises the supply and demand side, as shown in Fig. 3, by considering the new supply-side energy options, the energy reduction impacts of energy efficiency and the demand response on the electrical system. PLEXOS represents energy efficiency interventions/retrofits as power plants with specific characteristics. The energy audit showed that the organisation has six end uses, as presented in Fig. 10. All minor end uses that were not significant were grouped under the other end-use. The audit pointed out that 17 % of electricity can be reduced by installing efficient appliances for these six end-uses. The most significant savings can be realised by replacing compact fluorescent lamps (CFLs) with light-emitting diodes (LEDs) and replacing old inefficient HVAC units with new efficient ones. However, the audit only highlighted savings from replacing inefficient appliances with efficient technologies. It did not quantify any savings resulting from shifting the load to periods of low tariff periods. The energy-efficient appliances shown in Fig. 11 replace the inefficient appliances. Table A.1 presents the number of demand-side units installed and the related costs for efficient replacements. Fig. 12 shows the effects of installing efficient appliances on electrical demand.

3.5. Solar PV and wind technologies: hourly resource profiles

The study also optimises for shiftable demand that can be shifted to low tariff periods. However, the study only looks at the capacity that can be shif6+ted and does not develop operational details of the demand response strategies as in Ref. [45]. Therefore, further research is needed

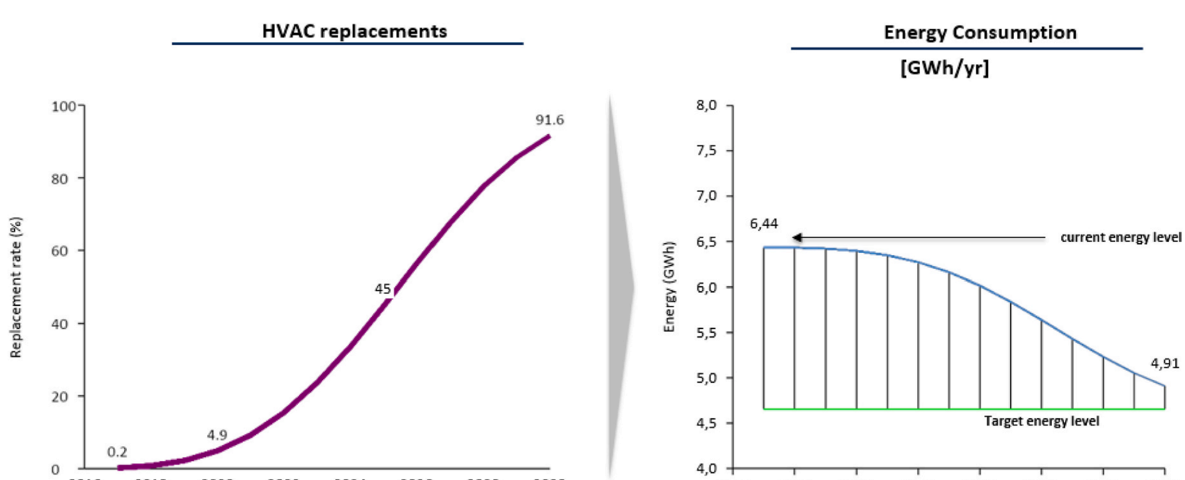

Fig. 8. HVAC stock replacement level and resulting energy efficiency savings.

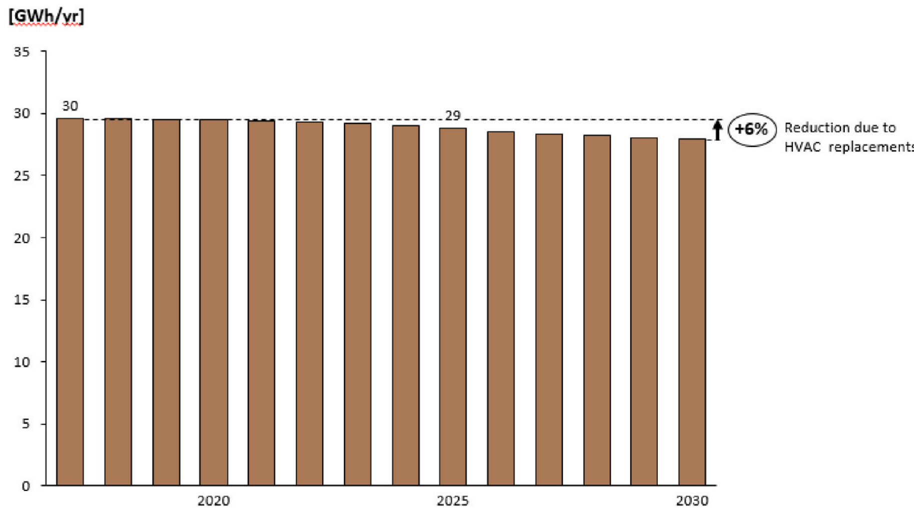

Fig. 9. Annual electricity demand forecast up to 2030.

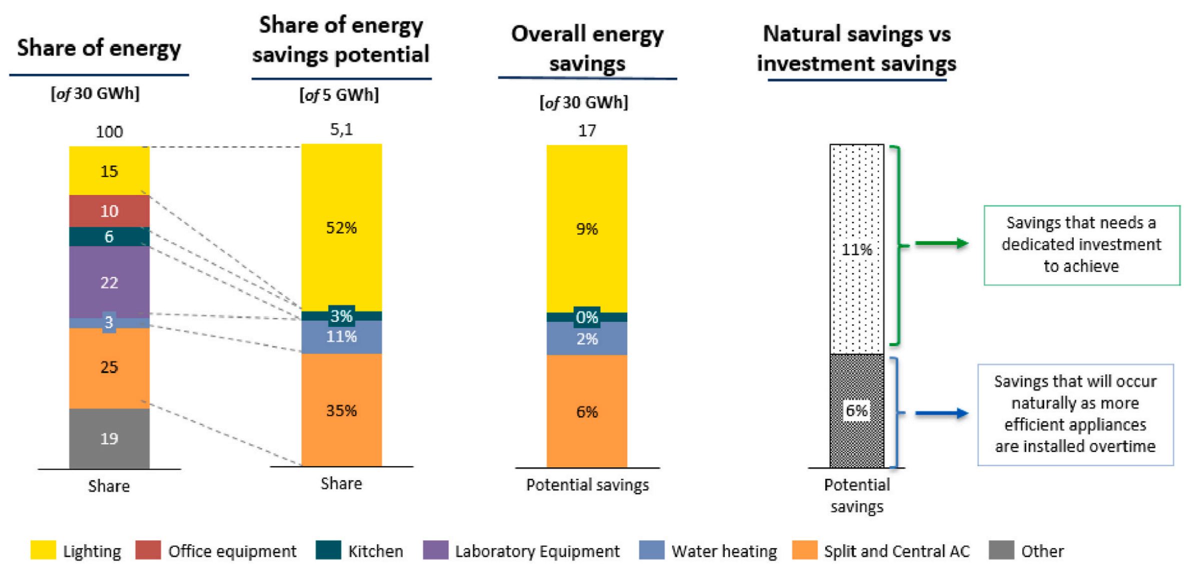

Fig. 10. End-uses within the organisation and potential energy savings.

to determine the operating schedule of the demand response strategy selected in this plan. In such research, demand response operating strategies will be designed to maximise financial benefits considering other issues, such as least effort and operational complexity [45–47]. Close to 50 units are centralised, and 2405 units are small office HVAC systems. Given the heterogeneity of the HVAC stock within the organisation, single-unit HVAC systems (small systems) and centralised HVAC systems will require different implementation strategies, excluding such operations. The current study highlights the LC capacity (in MW) that can contribute to the demand response strategies but does not develop those strategies.

Demand response assumes that the resource is free, but the optimisation includes the cost of enabling load shifting. The enablement cost consists of the controller, telemetry equipment, installation, programming labour costs, and maintenance costs [47]. The controller costs range from R300 to R7000 depending on the features needed on the programmed controller. According to this study, the shiftable load/demand is unlimited since the grid can provide all the ramping needs required.

The supply-side technologies considered in the planning are solar PV, batteries, wind, and biogas. For wind, solar PV, and biogas, it is paramount to have detailed information on resource availability as inputs into the modelling process. Based in Pretoria, the customer wanted to put all the options in one location, i.e., Pretoria, and all the resource assessments were done for Pretoria. However, as shown in Figs. 13 and 14, this site has a meagre wind resource, which is also highly variable in any given month. For every 1 MW of wind capacity installed, an average output of 0.2 MW is possible. The hourly wind speed information comes from the wind mast installed on the company premises. Eq. (10) calculates the hourly power generated from the wind speeds. Given that the national average wind capacity factor is 36 % [48], this is a meagre wind resource. In Fig. 13, the capacity factor is proportional to the wind resources. This is because wind resources are proportional to solar power generation.

$$P_w = \frac{\rho A v^3}{2} \tag{10}$$

with P_w is the hourly power from the wind speed, A is the rotor area of the 2 MW S turbine assumed for the organisation, ρ is the air density, and v is the wind speeds from the mast. For solar, the outlook is auspicious because for both North and East-West facing PV plants, for every 1 MW installed, about 0.6 MW is the output during most periods of the day, as

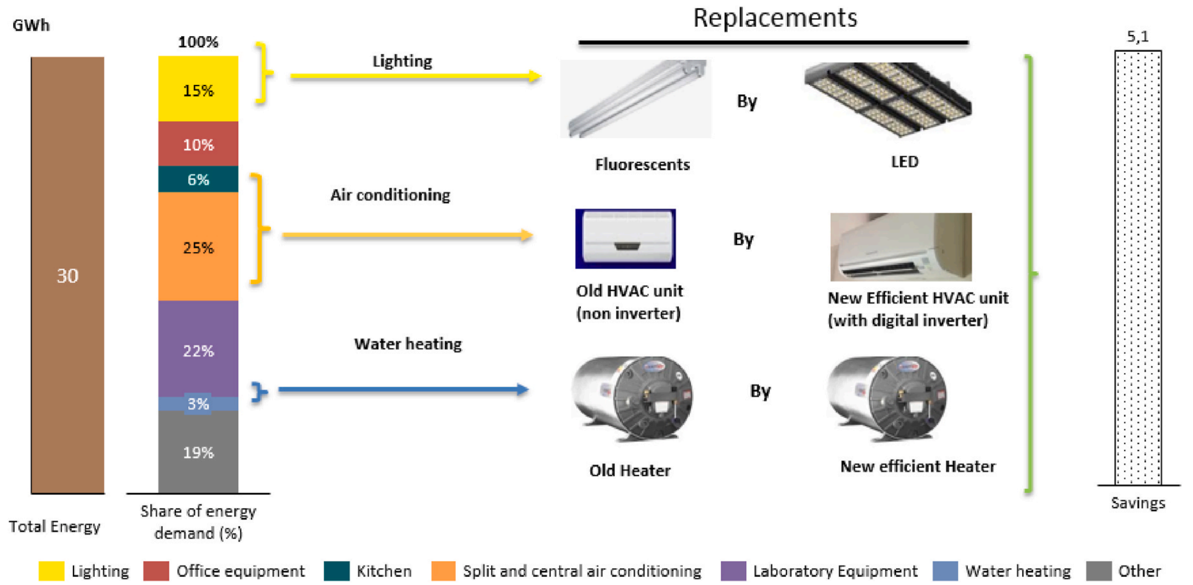

Fig. 11. Organisation's end uses and energy efficiency replacement options.

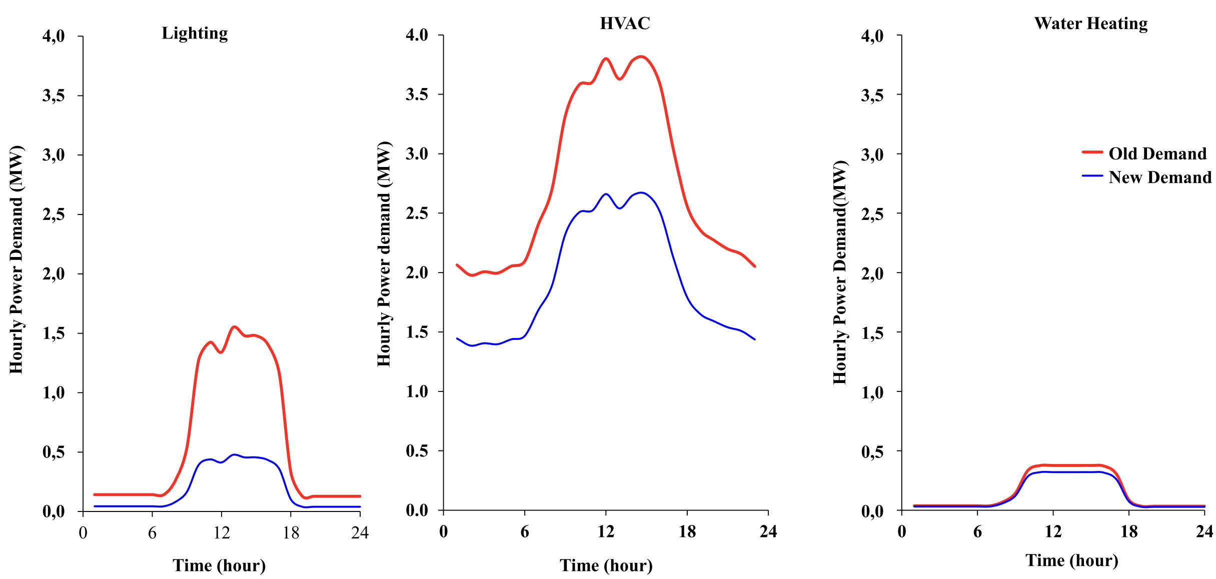

Fig. 12. Unit profile changes due to energy efficiency interventions.

described in Figs. 13 and 14. PV system was used to derive the power from a typical PV module.

3.6. Biogas power plant and waste resource availability

Fig. 15 gives the varying waste input streams that were assessed in the feasibility study. This design is the business perspective for a small biogas plant investigation. In conducting the PLEXOS optimisation, no gate fee for waste was assumed; waste is got for free from nearby shopping centres.

There are two proposed sites for biogas: site 1 with 10 000 m^2 and site 2 with 13 000 m^2. These two proposed sites (sites 1 and 2) can have a maximum biogas plant capacity of 1.5 MW and 1.95 MW, respectively. At these capacities, a daily waste loading of between 86 tonnes–112 tonnes per day is required to be delivered to the organisation or have such storage capability built on the campus, as shown in Fig. 16. The waste is to be sourced from businesses that deal with the trash within 50 km of the organisation. The economic performance of biogas is presented in Section 3.8.

3.7. Electricity tariff from the municipality

A fundamental assumption for this study is the future anticipated municipal electricity tariff. Although the tariff structure, as shown in Fig. 17, does not currently change, in this study, it is assumed that the tariff will increase by 2 % per annum for both energy and network charges. By non-changing tariff structure, the paper means that in 2030, the peak charges will occur at the same periods as in 2017. The differential increases and decreases between the Summer and Winter seasons will be the same.

Fig. 18 indicates the assumed average annual tariff increase over the study horizon. The study adopts an inflation rate of 5.5 %. The yearly accumulation was applied uniformly to the energy charges (volumetric charge) and network portion of the mega-flex tariff. The tariff trajectory is indexed to the organisation's LC scenario from the National IRP (IRP 2019) [49]. The feed-in tariff is assumed to increase from

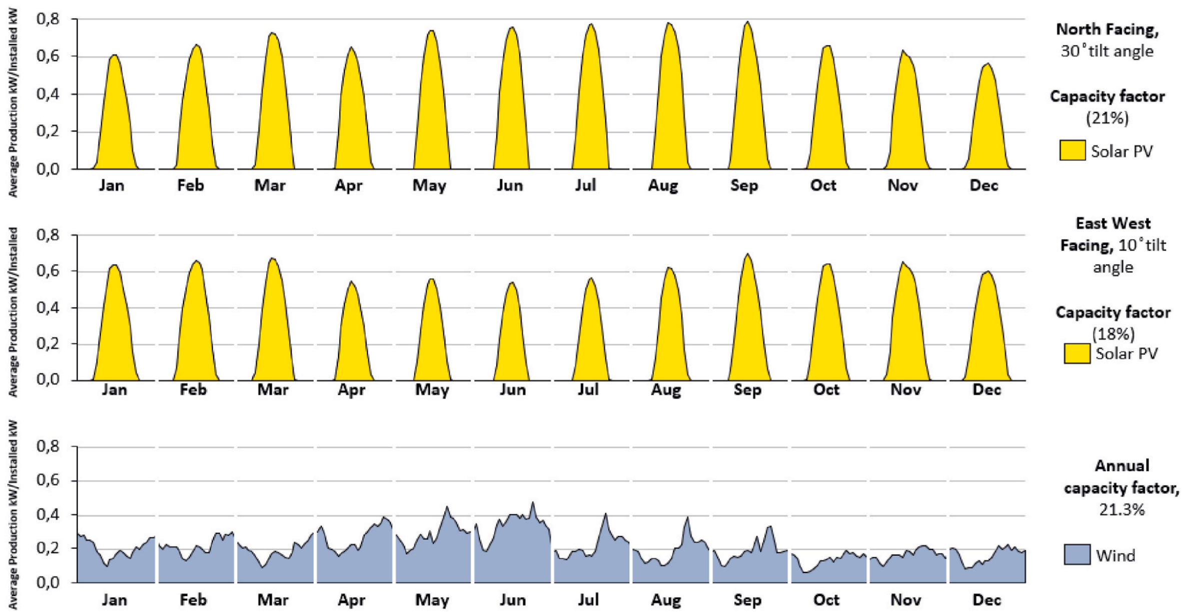

Fig. 13. Performance of existing solar PV plants on campus.

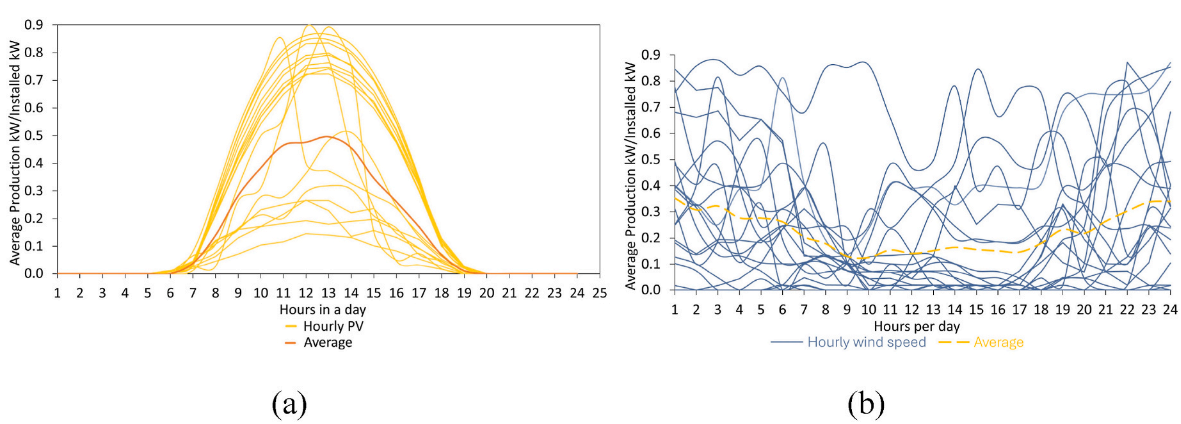

Fig. 14. Hourly resource profiles for input into PLEXOS: (a) solar PV, (b) Wind power.

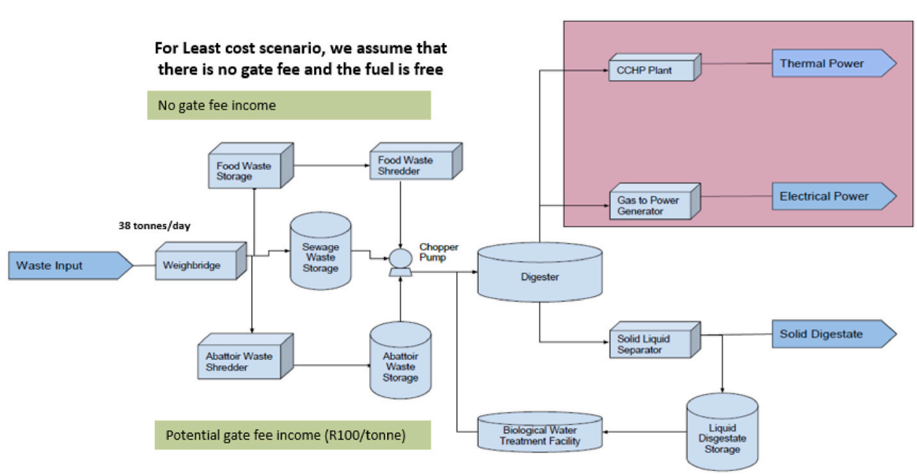

Fig. 15. Proposed design of the biogas plant.

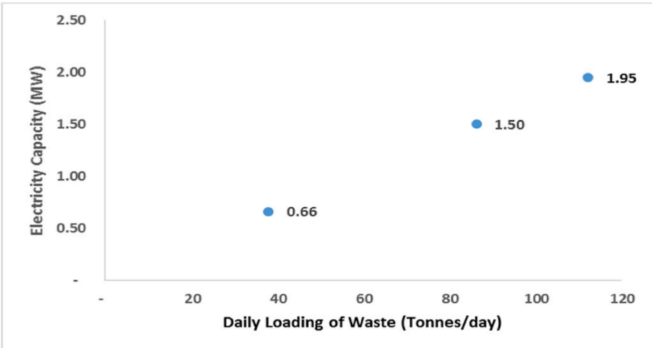

Fig. 16. Correlation of electrical capacity versus the needed waste for biogas generation.

$0.00625/kWh in 2018 to $0.0336/kWh in 2030 and stays constant.

3.8. Cost assumptions for the investment options

To inform the energy planning to be undertaken, a range of demand-side and supply technology costs and their expected evolution into the future need to be well understood (amongst a range of other input assumptions). Table A.2 shows the total and unit cost of installing energy efficiency and demand response technologies. For supply technologies, there are two broad categories of electricity systems costs. These are built costs, fuel costs, and fixed and variable operating and maintenance costs. These costs are used to calculate the levelized cost of electricity (LCOE), which Eq. (1) considers within the optimisation. The power generation costs influence the choice of new capacity built within the LP Plan of the PLEXOS simulation phase and the utilisation or dispatch of existing and new generators within the ST simulation phase. Wind and solar PV typically have high fixed costs and negligible variable costs. In contrast, conventional technologies have varying fixed-to-variable costs depending on their utilisation, as shown in Fig. 21 for the biogas plant.

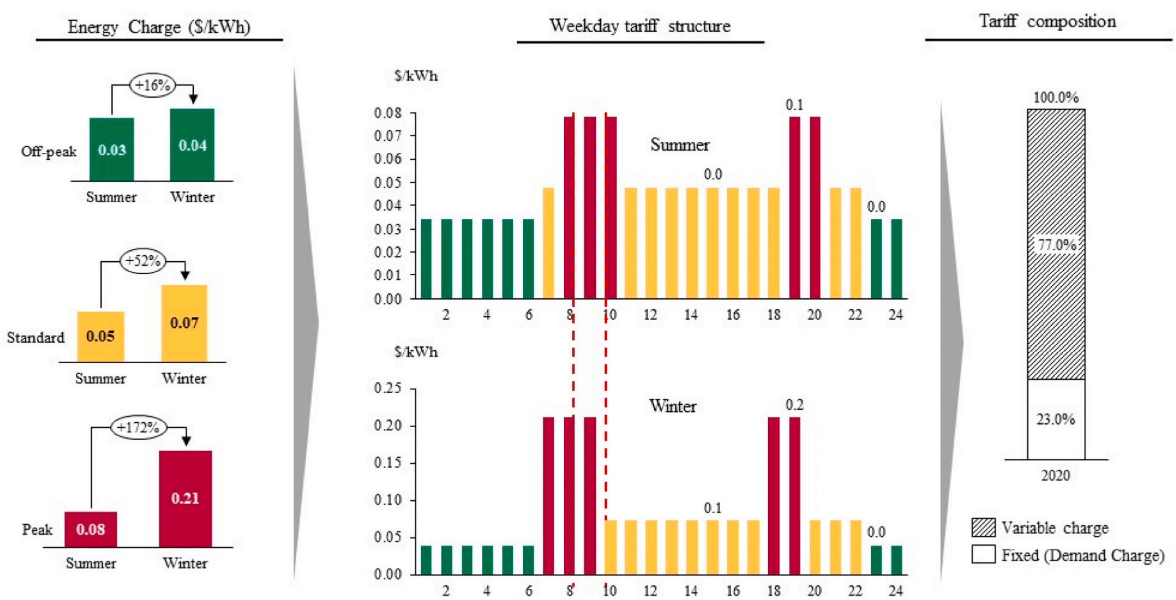

Fig. 17. Structure of current and future tariffs.

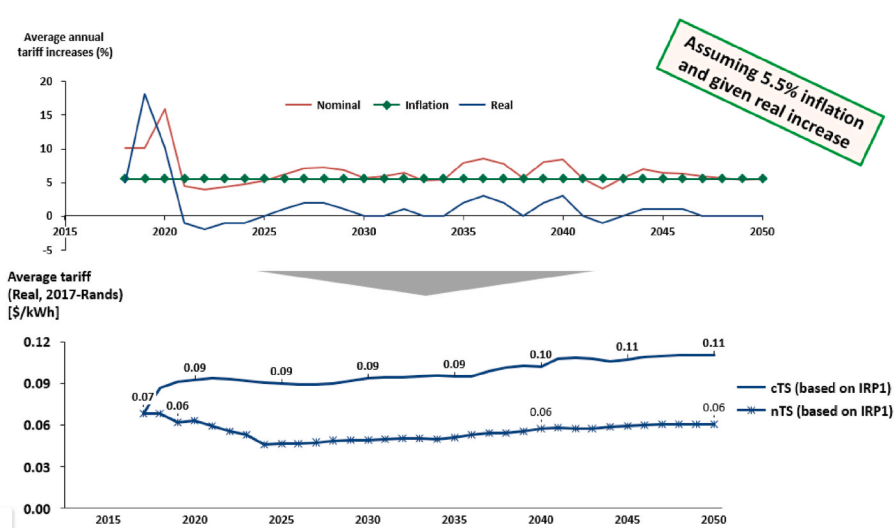

Fig. 18. Average annual tariff increases and average annual electricity tariff for current and future structures.

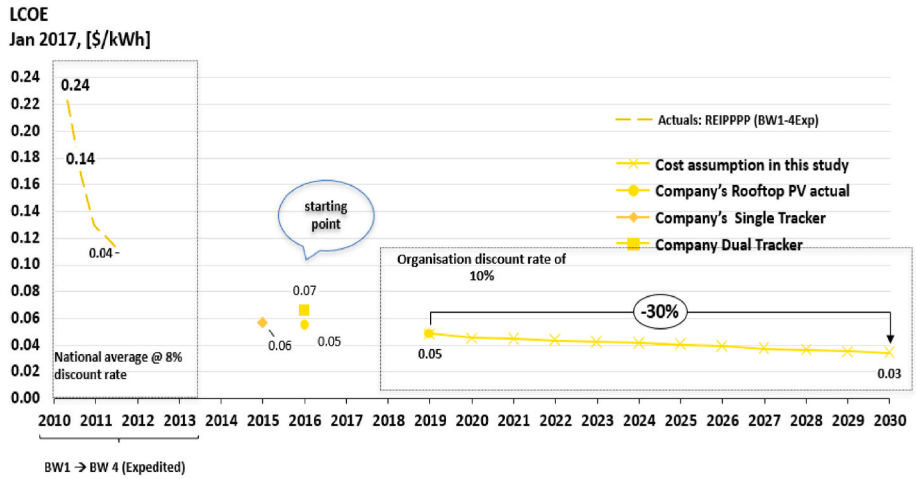

Fig. 19. Solar PV Investment costs (Installed and future assumed cost trajectory).

Before conducting this IRP study, the organisation had already procured its solar PV at LCOE between $0.065/kWh and $0.054/kWh from 2015 to 2017, as shown in see Fig. 19. Table A.3 presents the investment costs for existing PV plants. The investment and operating costs for batteries and other new supply options are shown in Table A.4 and Table A.5, respectively. By 2030, the investment cost for solar PV is expected to have dropped by 30 %, in line with international cost learning rates and reduction forecasts. The value of the lost load is $7/MWh as per [49].

Fig. 20 summarises the outcomes from the Renewable Energy Independent Power Producer Procurement Programme (REIPPPP) up to the latest Bid Window (BW) 4 (Expedited) announced in November 2015, while Fig. 21 presents the battery costs with an assumed initial from IRP2019. The future cost trajectory was estimated using learning rates of 10 % [40]. It is important to note that the REIPPPP costs include the shallow grid connection costs, including dedicated grid infrastructure costs and pro-rata contributions towards shared grid infrastructure.

The biogas design presented in Fig. 15 can operate in 3 modes – base power plant (providing power all the time to the campus), mid-merit mode (providing power only most of the time when the company has high tariff from the municipality) or purely during peaking periods to reduce the cost of using peak electricity. The tariff structure in Fig. 16 shows that the peak electricity within this municipality goes up to $0.2/kWh in the Winter season and is $0.08/kWh in the summer season. Depending on how the biogas plant is used, the cost of producing electricity with it differs based on its electricity demand profile. For example, suppose the plant operates as a peaking plant. In that case, it costs between $0.66/kWh – $0.60/kWh versus $0.13/kWh - $0.07/kWh when used as a mid-merit plant, as shown in Fig. 22. By power generation economics, baseload power stations are cheaper than peaking power plants. It can be seen also in the assessment of the small biogas that the company wanted to invest in. If the biogas were going to be used during peak times (short periods), the cost of electricity produced by it would be higher and vice versa. Appendix in Table A.5 presents additional cost data for the biogas plant.

4. Model calibration, validation and testing for reliability

4.1. Models validation and calibration

With the energy planning model, the critical validation is providing evidence that the models used are accurate in predicting the outputs. In Ref. [50] energy planning requires four types of model validations and their objectives are presented in Table 5.

4.2. Replication and calibration: calibration of survival curves for HVAC

Replication through calibration demonstrates the ability to model existing systems appropriately, hence validating the output [50]. This method is used to indicate that the survival curve rates used in this study

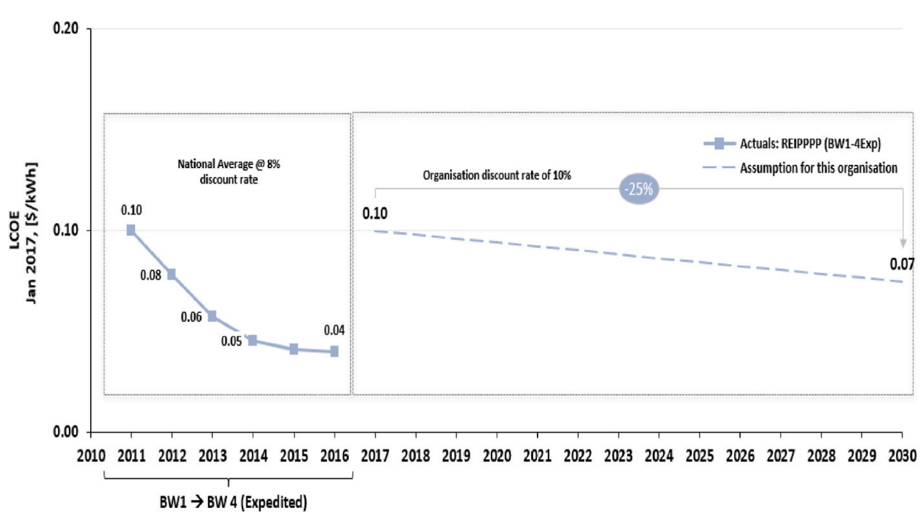

Fig. 20. Wind cost trajectory up to 2030.

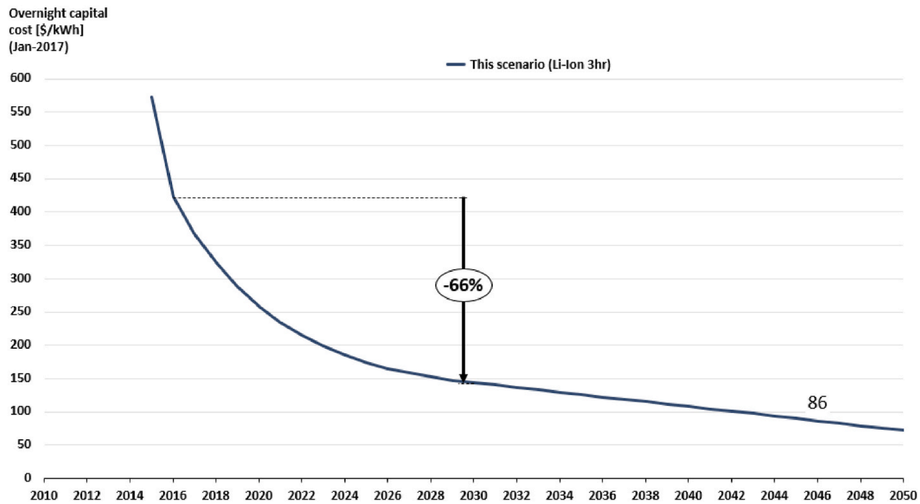

Fig. 21. Cost assumptions for the battery.

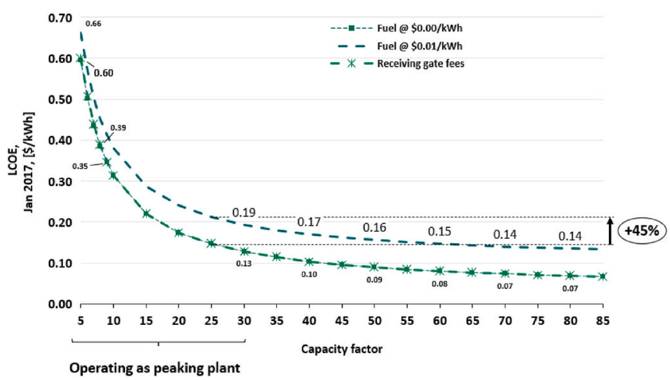

Fig. 22. The cost of producing electricity with biogas.

Table 5
Model validation techniques and their objectives.

Validation/ Verification Type	Short description	Equation #	Validation done	References
Replication and calibration	Testing the ability of the model/tool to replicate systems described with existing statistical/ actual data.	(6), (7)	✓	[50]
Validation through comparison	Compare results outputs with other studies	(6), (7)	✓	[50]
Theoretical validation	Testing model choice criteria	(8)	✓	[51]
Sensitivity analysis	Testing response to input assumptions		χ	[52]

are closer to what really happened. There is a paucity of data that can be used in South Africa to estimate the lifetime of HVAC units, as there are no annual appliance audits done for commercial or residential sectors. In the US, the US Energy Information and Administration office conducts two buildings-sector surveys—the Residential Energy Consumption Survey (RECS) and the Commercial Buildings Energy Consumption Survey (CBECS)—that provide rich data on equipment stock lifetimes, and energy consumption, etc within existing buildings [53]With such audit data from the surveys, deriving parameters for survival curves and estimating equipment lifetimes (a, q, and r) is simplified. In this study, the only data was the number of units replaced in recent years.

This number of HVAC units replaced was used to test the validity of the model in estimating appliance survival. The Facility Department (of the organisation used as a case study) had data on the number of HVAC units that were replaced in the 5 years prior to the study but did not know how far back (in years) those units were installed. In total, 396 HVAC units were replaced in the preceding 5 years (including the year of study), 269 of which occurred in the recent two years (122 in the year preceding the year of study and 147 in the year of study). Equation (11) was used to derive a survival curve based on this replacement data, which is shown in Fig. 23.

$$Survival\ Curve_{actual} = \frac{Un_t - Rep_{unit}}{Total_{units}} \tag{11}$$

Un_t is the total number of units being replaced, Rep_{unit} is the total number of units replaced, and $total_{units}$ is the number of units in stock. The survival curve closer to one derived using Eq. (6) data was assumed for this study. The calibration process was done by iteratively changing parameters (shape parameter-β, delay parameter – θ, and the scale parameter – α) and in Eq. (2) to closely match the survival curve based on actual data.

4.3. Validation through comparison: average lifetime of HVAC units

As shown in Eq. (2), appliance lifetime is one of the critical inputs to derive the survival curve for pieces of equipment. Equation (12) was used to derive the average lifetime for this study. This derived average

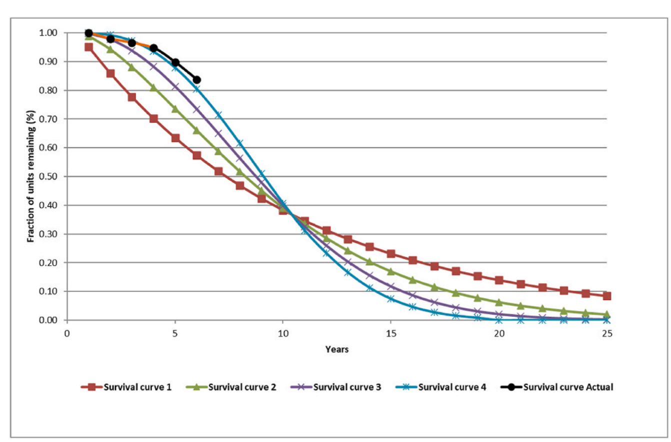

Fig. 23. Survival rates in comparison to actual replacements of HVACs.

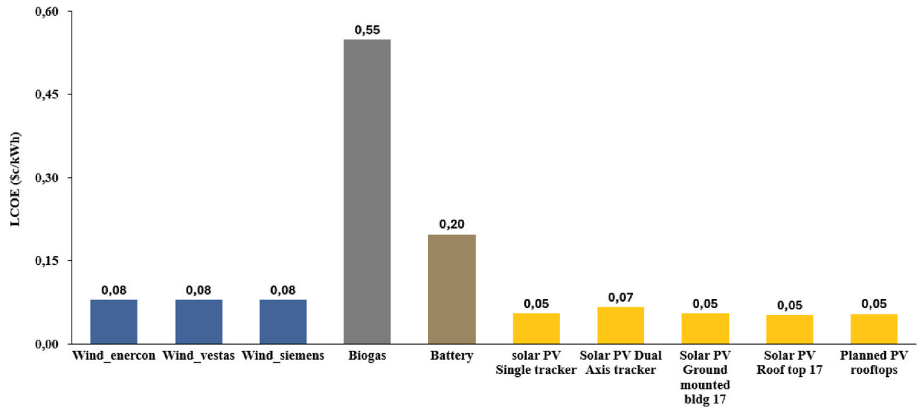

Fig. 24. Levelised cost of energy for technologies assessed in the model.

Table 6
Comparison of survival curve parameters and average lifetime for HVAC with other studies.

	β	θ	x	α	Average lifetime (y)	Validated using
US Study: HVAC units [55,56]	2.094	0	T1 - T50	21.49	19	$M_{HVAC} = \theta + \alpha(\ln(2))^{1/\beta}$
This Study	2.600	0.5	T1 - T25	9.90	13	$M_{HVAC} = \theta + \alpha(\ln(2))^{1/\beta}$
ASHRAE HVAC units [54]					10–15	Actual survey data

lifetime was compared to the average lifetimes of the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE). A typical HVAC unit has an average lifetime between 10 and 15 years [54] and studies in Refs. [55,56] have shown an average lifetime of 19 as presented in Table 6. By iteratively changing parameters (shape parameter-***β***, delay parameter – θ, and the scale parameter – α) and matching the survival curve to the one derived from actual data, 13 years is the average lifetime for HVAC in this study.

$$M_{HVAC} = \theta + \alpha(ln(2))^{1/\beta} \tag{12}$$

4.4. Theoretical validation: technology choice based on LCOE

The PLEXOS modelling tool makes technological choices based on the levelized cost of energy. It is critical to test the validity of such a choice using the LCOE of different technologies within the model (intra-model validation). This is expressed in Eq. (13). As presented in Fig. 3, it is clear that biogas and batteries are expensive throughout the modelling period (2017–2050), so it will not be economically viable for them to form part of this organisation's portfolio. The model optimises to meet the demand with the least cost within a scenario.

$$LCOE_{tech} = \frac{NPV_{costs}}{NPE_{tech}} = \frac{\sum_{t=1}^{n} \frac{C_t + O_t + V_t}{(1+df)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+df)^t}} \tag{13}$$

$LCOE_{tech}$ is the levelized unit cost of producing electricity with a particular technology under consideration. NPV_{costs} is the net present value of costs, and NPE_{tech} is the net present value of energy produced or saved by an intervention. N is the number of years the technology will be in service, C_t is the capital cost, O_t is the operational cost, V_t is the variable cost, and df and t represent discount rate and year t, respectively. E_t is the energy produced or saved by an intervention.

The biogas plant could only make economic sense if it were used as a baseload plant, as shown in Fig. 14. The cost of producing electricity with biogas will be lower than the cost of municipal electricity only when the biogas plant production is maximised and is used at availability of 80 % and above. Therefore, a biogas plant will only make economic sense if it replaces municipal electricity and is run as a baseload power plant, feeding the business with power more than 80 % of the time. Given that biogas technology does not have a decreasing learning rate, this can only occur with the tariff increase above the assumed tariff increase presented in Fig. 17.

With these validation and calibration processes, it has been proven that the model provides a reasonable selection of technologies to form the portfolio of electricity-generating assets for this business.

5. Results and discussion

To explicitly show the cost implications of implementing and not implementing the vision, scenarios described in Section 3.1 compare these future outlooks. In all the scenarios, the power plants can be built until 2050. The model is setup assuming perfect oversight: known future load demand and costs, tariffs and costs assuming learning rates for solar, wind and renewable energy technologies and batteries.

5.1. Business as usual

The BAU scenario in Fig. 25 presents the organisation's future electricity demand, associated operational (municipality bill) and maintenance costs with a current asset portfolio of 1.1 MW. No new additional electrical capacity has been built, except for the additional 0.9 MW of solar PV currently under construction, which is within the planning horizon (2027–2050). The decommission starts from 2040 onwards.

The municipal power meets 88 % of the organisation's electricity demand from 2019 up to 2036. The NPV of the total electricity costs over the whole study horizon is approximately.

$24.2 million, equating to an equivalent annuity of $2.6 million/year over an 11-year horizon (2019–2050). The total electricity cost includes the total cost of electricity generation (municipal tariff costs) and fixed operations and maintenance costs for the existing solar PV.

Fig. 26 presents hourly generation from organisation supply capacity and municipal imports on a typical Summer week. The hourly dispatch profile shows how solar PV meets the organisation's peak demand, which occurs in the middle of the day during weekdays. Energy efficiency and demand response are not implemented under this scenario.

5.2. Least cost–current tariff structure (LC cTS) with DSM consideration

The least cost (LC) scenario considers the same input assumptions as in the BAU scenario, with an additional option to install new supply and demand (energy efficiency and demand response) capacity from 2020

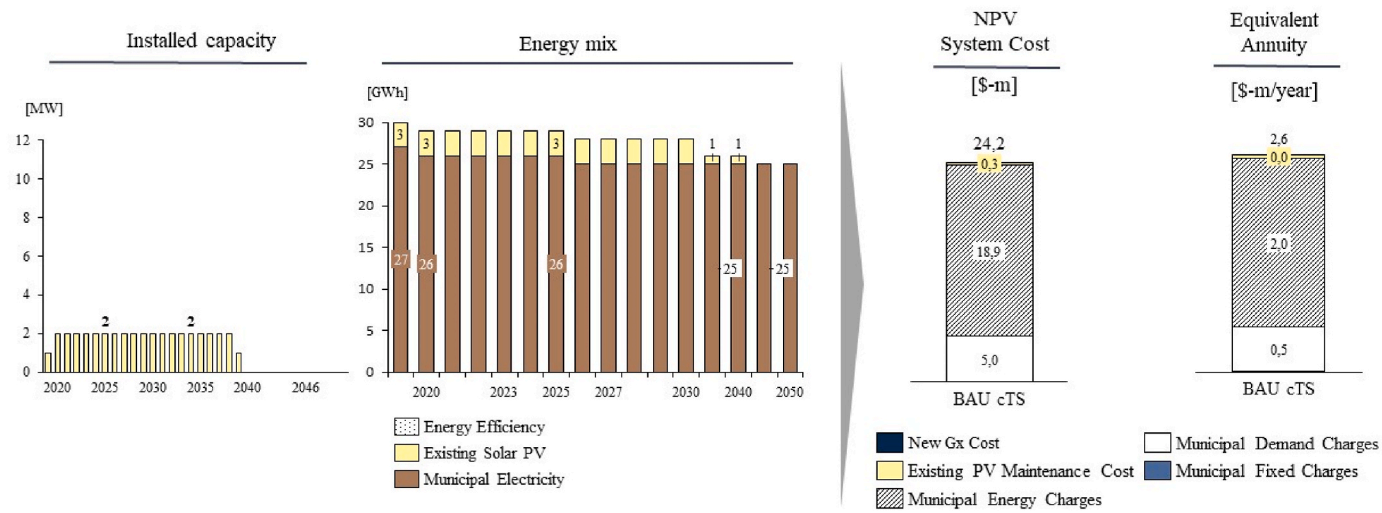

Fig. 25. Business as usual Scenario outlook into the future.

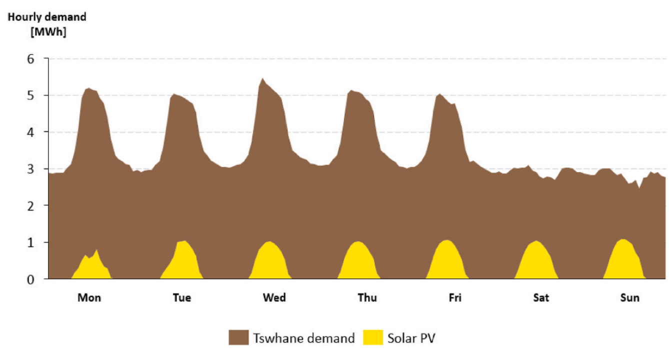

Fig. 26. BAU - Hourly total generation for a summer week in 2030.

onwards, summarised in Section 3.1 in Table 4. The LC with the current tariff structure assumes the current tariff structure, as presented in Fig. 16, will not change in the future; only an annual increase of 2 % is assumed. The feed-in tariff is supposed to increase from $0.01/kWh in 2018 to $0.03/kWh in 2030 and stays constant after that.

The installed capacity and energy from the organisation's existing generation capacity and the energy contribution from the municipality are shown in Fig. 27. Under the assumed tariff trajectory, wind, biogas, and battery storage are still not the least cost and cost-effective to invest in. By 2020, an additional 2 MW of solar PV will be added to the organisation's electrical system. By 2025, the new solar PV capacity will have increased to 4 MW, ultimately resulting in 7 MW of solar PV capacity by 2027.

All energy-efficient lighting and geyser technologies are economic to install as early as 2020, while installing efficient HVAC units is not. The efficiency gains from HVAC systems will only come from the HVAC replacement strategy explained in Section 3.2. HVAC systems are not economical compared to other technologies because the LCOE for HVAC is $0.07/kWh for every unit of electricity saved. This LCOE cannot compete with the cost of solar PV during the day because the cost of saving 1 kWh from an HVAC system is costlier than producing a unit of electricity from the solar PV system.

Although energy-efficient HVAC units are not economic to install for this organisation, their electricity demand can be shifted to low tariff periods, as shown in Fig. 28. By implementing a demand response (load shifting programme), the cost of the least cost scenario reduces by 10 % compared to the BAU Scenario. Fig. 28 shows that shifting 1.1 MW from the morning peak tariff period to the off-peak period is economical. The price of electricity is $0.08/kWh during the peak period, while the price is $0.03/kWh during the off-peak peak. Therefore, shifting 0.5 MW of the demand to an earlier standard tariff period in the evening peak is

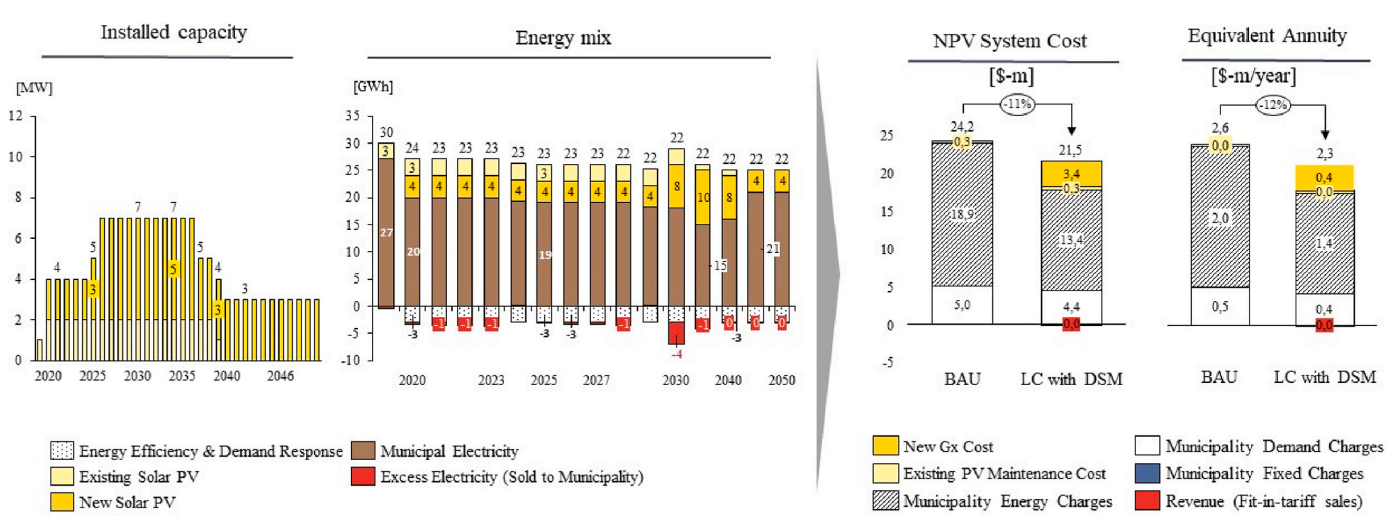

Fig. 27. Installed capacity, energy, net present value and an equivalent annuity of the total electricity costs for the LC (LC cTS) scenario.

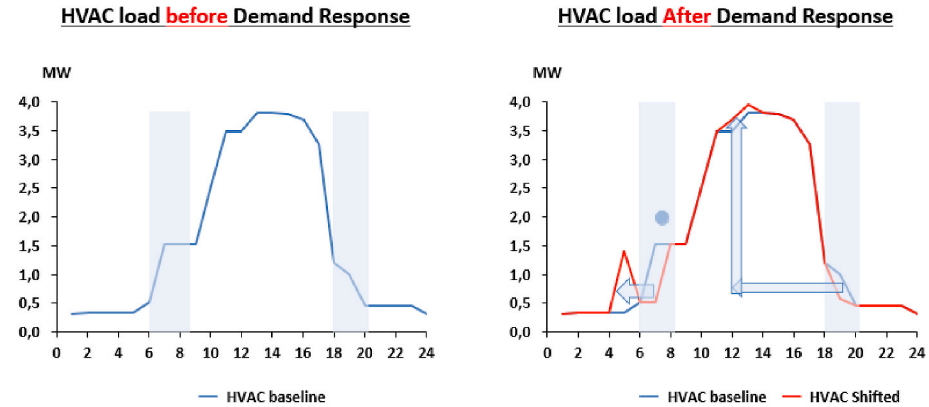

Fig. 28. Typical load before demand response implementation and after demand response implementation.

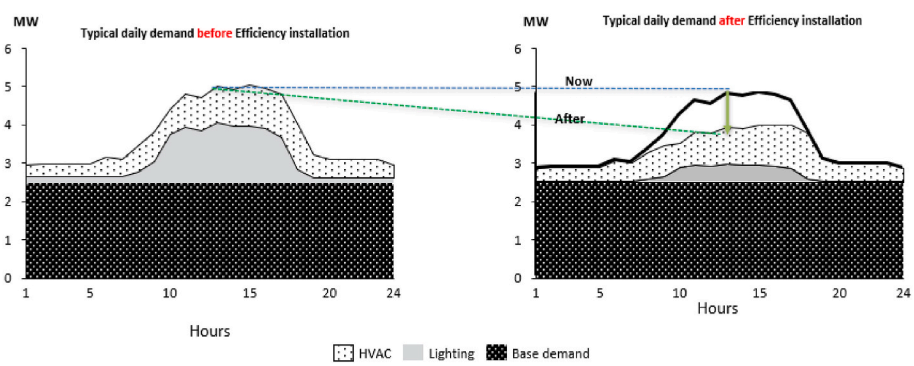

Fig. 29. Typical load after energy efficiency intervention installations.

economic. Shifting the electricity demand to the time during sunlight hours enables the demand to be met with power generated from PV.

After installing the efficient lighting and water geysers, Fig. 29 shows the electrical load profile will be lower and peaking at 3.5 MW instead of the current 5 MW. Lighting has the most significant efficiency savings. Relative to the lighting baseline demand, for every CFL replaced with LEDs, 68 % of lighting electrical energy is saved. In Figs. 29 and 5% of the load reduction comes from efficient water heating geysers, while 95 % comes from efficient lighting installation.

By 2030, solar PV will meet 36 % of the organisation's demand from optimised energy technologies. Therefore, Fig. 27 shows that the annual electricity imports from the municipality will contribute 54 % to the organisation's electricity demand by 2030. The NPV of the total electricity system costs $21.5 million over the entire study horizon. This total cost equates to an equivalent annuity of $2.3 million/year over the next 30 years. The total electricity cost includes the total cost of electricity generation (municipality tariff costs), fixed operations and maintenance costs for the existing solar PV investment and operating costs of the new solar PV, and energy efficiency and implementation of the demand response. Thus, the LC cTS scenario reduces the organisation's electricity bill by $0.3 million per annum for the next 30 years relative to the BAU scenario. The LC Scenario is 11 % cheaper than the BAU Scenario.

The energy efficiency interventions will save about $0.15 million annually. In contrast, demand response will save the organisation about $9375 annually, and the savings from installing new PV is $0.165

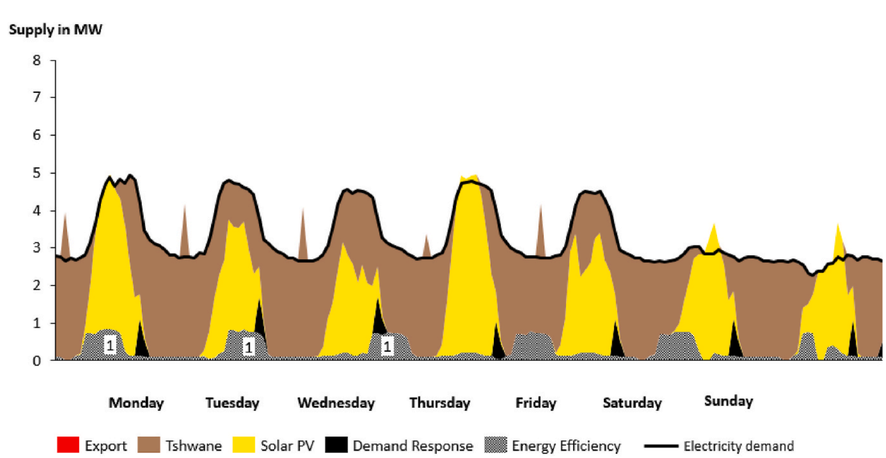

Fig. 30. Typical weekly load in 2030 under the LC scenario with DSM measures.

million. Therefore, new PV generation saves 50 % of the total system cost, while 47 % is from energy efficiency. A mere 3 % comes from demand response savings (shifting the HVAC loads from peak to off-peak periods, as shown in Fig. 30.

Fig. 30 shows that the model (PLEXOS) sometimes shifts the load far ahead of time (2–5 h) before the usual demand for that service – HVAC. This extended shifting occurs because the model does not consider the payback effect [57]. According to the payback effect theory, if the heating output reduces for a couple of hours and the temperature lowers below the set temperature points, the subsequent heating demand will increase slightly above the case where the temperature was not allowed to drop too low. This phenomenon adds more complexity to the problem as the control mechanism needs to manage these side effects. PLEXOS's objective function is only concerned with cost minimisation.

5.3. Least cost–current tariff structure (LC cTS (no DSM) without DSM consideration

If the organisation did not pursue DSM, the total installed PV installed capacity would amount to 9 MW. However, the cost of such a system would be $0.1 million higher annually compared to the LC scenario that incorporates demand-side management interventions, as outlined in Figs. 25 and 31. In the absence of energy efficiency and demand response implementations, Fig. 31 demonstrates that installing an additional 7 MW of PV within the organisation by 2030 is the most cost-effective option.

The net present total system cost is $23.8 million over the planning period, resulting in $2.5 million per annum. This cost is 2 % higher than the LC scenario that considers demand shifting (demand response) of the HVAC units and installing efficient lights. Some significant solar will be curtailed or sold to the municipality in days with an excellent solar resource, as shown in Fig. 32.

As highlighted in Ref. [36], once a microgrid is connected to the grid, the grid serves as a battery. Therefore, the battery competes with the grid electricity in this case study. Battery systems are still expensive throughout the planning period compared to the electricity tariff from the municipality during the same period.

6. Conclusions

The main findings of this research indicate a shift in investment priorities for reducing electricity bills. Energy efficiency is no longer the primary consideration before exploring supply-side technologies. The significant decline in solar PV costs has made it the LC intervention for typical commercial sector customers, especially those on a time-of-use municipal tariff like the one analysed in this study. The study assumes the same load shape throughout the modelling period.

The advantages of solar PV are further enhanced as most customers experience peak demand when solar PV generation is at its highest. Therefore, increasing the rollout of solar PV is an investment strategy that offers significant benefits, especially when combined with lighting retrofits. It should be noted that efficient HVAC systems are not the most economic investment option for the entire modelling period, as no learning effect is assumed for HVAC units in any scenario, as saving one unit of electricity from HVAC is more expensive than generating the same unit using solar PV.

This work emphasises the need for utilities to prioritise supply- and demand-side interventions rather than solely focusing on energy efficiency measures. Assessing energy efficiency and supply-side technologies concurrently provides a comprehensive understanding of the most effective economic policies to implement. Taking a holistic approach by considering both aspects simultaneously is the recommended approach.

In this context, the integrated resource planning framework utilised in this study offers a valuable tool for assessing energy interventions aimed at long-term electricity bill reduction for customers. This framework should not be limited to utilities at the national level and should be adopted by a broader range of stakeholders. In the past, energy efficiency interventions with a return on investment of 5–7 years were considered low-hanging fruit for immediate energy savings. However, with the decreased costs of solar PV, installing a solar PV system now offers greater value than replacing an inefficient HVAC unit. The results show that the commercial entity can save their electricity bill by $0.16 by installing 6 MW solar PV over the lifetime of the solar PV plants. It is worth highlighting that despite the significant reduction in the cost of wind energy, installing a wind turbine within the organisation's energy mix was still not economical. This is primarily attributed to the low wind resources available at the site. The limited energy resource profile resulted in a higher levelized cost of electricity production from the wind turbine than the cost of power supplied by the municipality, as shown in Fig. 24.

Therefore, it becomes evident that the cost of technology and the availability of an adequate energy resource are crucial factors to

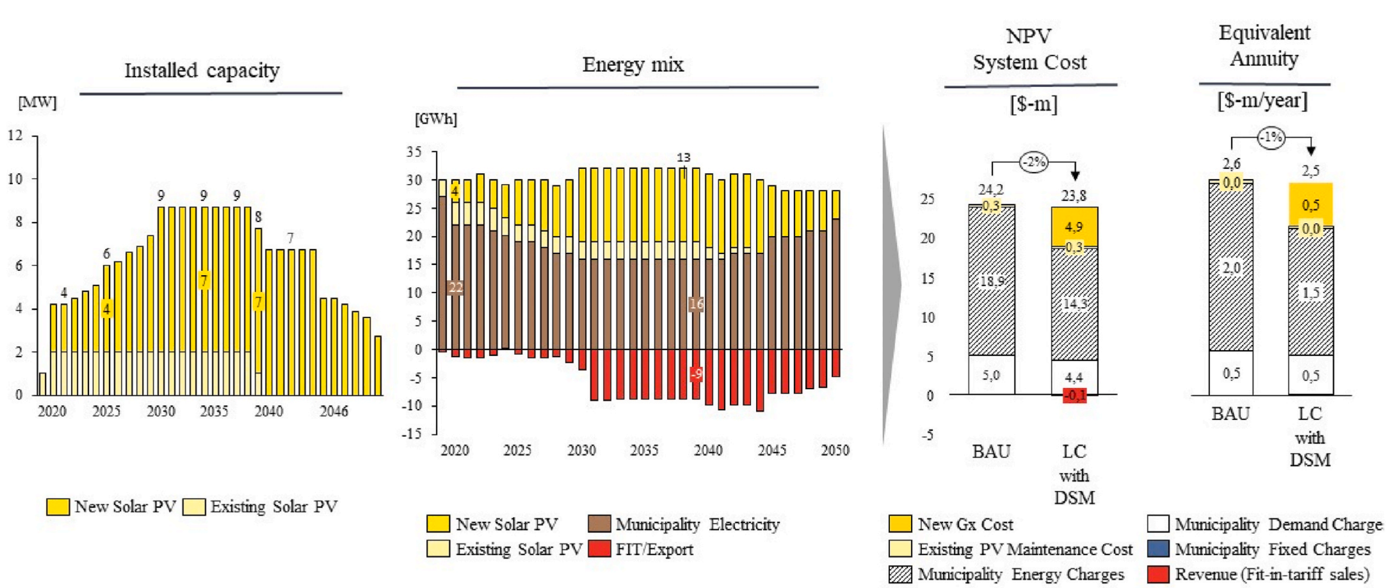

Fig. 31. Installed capacity, energy, net present value and an equivalent annuity of the total electricity costs for the LC (LC cTS) scenario without demand-side management.

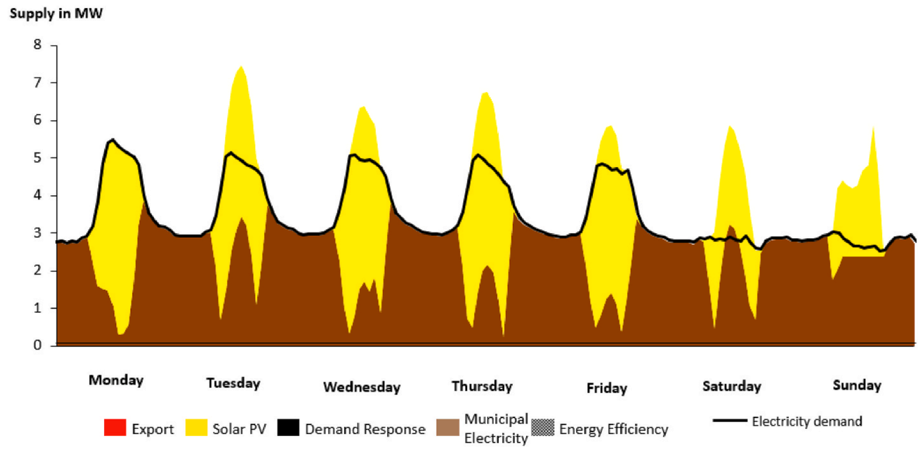

Fig. 32. A typical dispatch profile under an LC scenario without DSM.

consider when designing an energy plan. It is essential to acknowledge that the reported energy efficiency savings from retrofits assume no changes in user behaviour. Therefore, the results presented in this study do not account for rebound effects on DSM measures. For instance, if offices modify their lighting or HVAC usage patterns, the savings derived from load shifting and energy efficiency interventions may differ from the quantifications provided in this study due to rebound effects. The maximum load that can be shifted for HVAC units during periods of low tariff costs is 1.4 MW. Additional studies are needed to comprehensively quantify the operational strategies and benefits associated with demand response from HVAC units.

This study assumed perfect foresight of load, and with demand response, the load will be dynamic because the future load will be a function of people coming into the building and temperature and their needs for heating and ventilation. Studies that incorporate load-shifting strategies must also look at changes in load shape in subsequent years.

CRediT authorship contribution statement

Mamahloko Senatla Jaane: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ramesh C. Bansal:** Writing – review & editing, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Raj M. Naidoo:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Nsilulu T. Mbungu:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Unarine Bridget Mudau:** Writing – review & editing, Visualization, Validation, Software, Methodology, Investigation, Formal analysis. **Teslim Yusuf:** Writing – review & editing, Visualization, Methodology, Investigation, Funding acquisition. **Keorapetse Kgaswane:** Resources, Validation, Writing – review & editing. **Prathaban Moodley:** Resources, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A.1
Input assumptions for demand response

Parameter	Units	HVAC	Water Heating
Installed Units	Number	2462	191
Installed capacity	kW	6249	379
Capacity participating in DR	kW	1000	200
Units participating in DR	Number	394	101
DR Participation Level	%	16 %	53 %

Table A.2
Input assumptions for energy efficiency options

Parameter	Units	Lighting	HVAC	Water Geyser
Total investment (appliance and installation) cost	$	490 479	831 803.13	47 686
Existing installed capacity	kW	2185	6249	379
Installable efficient capacity	kW	387	3272	195
Overnight cost	$/kW	1267.36	208	236
Energy saved	GWh	3	2	1
Unit energy consumption (UEC)	kWh/yr.	88.6	2614	4065
Number of appliances	Units	43 865	2462	191
Number of replaceable units	Units	43 216	1905	154
Lifetime	Years	8	12	5
Appliance unit cost	$/unit	11.375	436.625	4779
LCOE ($/kWh saved)	$/kWh	0.0344	0.069	0.0225

Table A.3
Cost of existing solar PV plants

Property	Units	Renewables			
		Single Axis Tracker	Dual Axis Tracker	Building 17 Rooftop system	PV Phase 1
Rated capacity (net)	(MW)	0.56	0.20	0.25	0.91
Total construction time (2017)	($ Million)	1100.94	2045.56	1161.4	946.31
Fixed O&M	($/kW/year)	20.4	19.5	14.44	14.44
Construction time	(Years)	0.5	0.5	0.5	0.4
Load factor (typical)	(%)	21 %	24 %	20 %	20 %
LCOE	($/kWh)	0.052	0.0625	0.0544	0.048
Technical life	Years	25	25	25	25

Table A.4
Cost of battery technologies

Property	Units	Storage Technologies Battery (Li-ion,1h)	Battery (Li-lon, 3h)
Rated capacity (net)	(MW)	2	2
Total construction cost (2017)	($/kW)	618.2	1518.8
Total construction cost (2030–2050)	($/kW)	618.2	1518.8
Construction time	(Years)	0.2	0.2
Capital cost (calculated) (2017)	($/kW/year)	618.2	1518.8
Capital cost (calculated) (2030–2050)	($/kW/year)	618.2	1518.8
Fuel cost	($/GJ)	0	0
Heat rate	(GJ/MWh)	4045	4045
Round-trip efficiency	(%)	89 %	89 %
Fixed O&M	($/kW/year)	38.625	38.625
Variable O&M	($/MWh)	0.1875	0.1875
Load factor (typical)	(%)	4 %	12 %
Lifetime	(Year)	15	15

Table A.5
Cost and performance characteristics of new supply options

Property		Renewables				
		Wind	Solar PV (Tracking)	Solar PV (Fixed)	Solar PV (Rooftop)	Biogas
Rated capacity (net)	(MW)	2–3	1	1	1	1
Overnight cost per cap capacity [2017]	($/kW)	2157.8	1204.1	1100.93	963.375	3469.75
Construction time	(Years)	0.5	0.5	0.5	0.4	1
Capital cost (in 2017 + 6 Value)	($/kW/year)	253.44	132.63	121.31	104.25	382.25
Technical life	Years	20	25	25	25	25
Fuel cost	($/GJ)	–	–	–	–	0
Heat rate	(GJ/MWh)	–	–	–	–	20 000
Fixed O&M	($/kW/year)	365.625	20.38	12.5	14.44	0.0625
Variable O&M	($/MWh)	–	–	–	–	536
Load factor (typical)	(%)	21.3 %	21 %	20 %	20 %	85 %
Minimum Up Time	hrs	–	–	–	–	1
Minimum Down Time	hrs	–	–	–	–	1
Maximum Ramp Up	MW/min	–	–	–	–	0.01
Maximum Ramp Down	MW/min	–	–	–	–	0.02
Maintenance rate	(%)	–	–	–	–	2 %

(*continued on next page*)

Table A.5 (*continued*)

Property		Renewables				
		Wind	Solar PV (Tracking)	Solar PV (Fixed)	Solar PV (Rooftop)	Biogas
Forced outage rate	(%)	–	–	–	–	1 %
Mean Time to Repair	hrs	–	–	–	–	8
Max Time to Repair	hrs	–	–	–	–	168
Min Time to Repair	hrs	–	–	–	–	1
CO_2 emissions	kg/MWh	–	–	–	–	670
NOx emissions	kg/MWh					1
CH_4 emissions	kg/MWh					201
Particulate emission	kg/MWh					2

Data availability

Data will be made available on request.

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