Preprint of paper accepted at Energy for Sustainable Development
https://doi.org/10.1016/j.esd.2019.03.004

Combining grid-tied PV and intelligent water heater control to reduce the energy costs at schools in South Africa

S. Gerber[a], A. Rix[a], M.J. Booysen[a,*]

[a]*Department of E&E Engineering, Stellenbosch University, South Africa*

Abstract

South Africa's escalating electricity rates are increasingly diverting educational resources to utility bills. Recent advances in solar PV affordability, the advent of the smartgrid and the capacitive nature of water heaters could be combined to enable new methods for electricity cost and efficiency management without affecting user comfort. Control methods that combine excess PV energy dumping and real-time temperature-based prioritised scheduling were compared with the normally-employed thermostat control. In addition, the performance of an energy-optimising approach is compared with a peak demand optimising approach. The results show that peak demand limiting with a two-temperature thermostat provided the highest cost saving with a 30% reduction of the school's electricity cost and only a 0.2 percentage point reduction in the number of warm water events.

Keywords: Solar energy; Thermal energy storage; School energy cost; Electric water heater; Scheduled control; Cost saving.

1. Introduction

Global energy consumption is expected to increase with accelerated growth in developing countries (Energy Administration, 2016). Because of the surge in demand worldwide, many utility companies will be forced to impose increased tariffs to fund their development (Energy Administration, 2016). In South Africa, Eskom is the largest utility company, generating approximately 95% of the country's electricity demand (Eskom, 2018). However, the South African energy mix depends on coal for 70% of generation (Department of Energy, 2018). Due to a poor development strategy and lack of government funding, the energy demand at certain peak times could not be met and led to the country's power supply crisis from 2008 until 2013, and again in 2018 Eskom applied for three consecutive 15% yearly tariff increases to combat the country's energy supply shortage (Chudy et al., 2015; Baker and Sovacool, 2017; IoL, 2018; Smit et al., 2019). During the five-year period from 2008, a cumulative tariff increase of 114% was approved by the national energy regulator to facilitate the increase in electricity generation capacity, anticipated national campaigns and demand-side-management (DSM) programs (Deloitte, 2017). These rising energy costs have placed a financial burden on poorer communities, with many municipalities accumulating debts to the energy supplier, which in turn led to accelerated tariff increases, affecting more municipalities and placing further constraints on already restricted local economies (Baker and Sovacool, 2017; Smit et al., 2019). As a result of the high cost, numerous unsafe and illegal power connections are made, and local governments are forced to divert public funds to pay off debts (COGTA, 2017).

The educational sector in South Africa is by no means unaffected by the crisis and soaring costs. Public education in South Africa receives the largest yearly national budget contribution, with more than 240 billion rand to be spent in 2018 (National Treasury, 2018). However, nearly 75% of the allocated education budget will go towards employee compensation, with less than 10% assigned to subsidies and new school building infrastructure (National Treasury, 2018). This has put pressure on schools to replace failing infrastructure, while paying increasing municipal bills. Reducing the financial strain placed on schools is therefore imperative, according to the Thebe report (COGTA, 2017). This relief could come by employing alternative energy

*Corresponding author
Email address: mjbooysen@sun.ac.za (M.J. Booysen)

generation methods such as solar power or through the introduction of smart technologies such as envisaged in smartgrids.

Driven by technological advances, economies of scale and deployment subsidies the installation costs of solar power has declined (Hirth, 2015; Baker and Sovacool, 2017). However, many organisations (e.g. Departments of Education and Public Works) still lack the necessary resources required to determine the benefits of renewable energy solutions, particularly due to the complexity involved in determining an accurate cost versus benefit forecast, as it will vary on a case by case basis (Sedibe, 2011). Another challenge faced when designing solar systems, is that it may provide excess energy during certain times of the day in certain seasons or load conditions, and effectively managing excess supply to achieve maximal benefit requires thoughtful considerations and planning (Osuri et al., 2015).

Schools provide the potential benefit of having their weekday peak power demand profile coincide with peak solar PV generation curves, while being billed to a demand-based tariff structure (Stellenbosch Municipality, 2018). Demand charges are billed once per calendar month depending on the monthly peak power demand, and is employed by a number of schools in the country. The school evaluated during the study is shown in Figure 1, with the areas for optimal PV installation highlighted.

Managing the power demand of buildings to reduce their energy footprint has been a widely discussed topic as the interest in energy saving and clean energy continues (Hida et al., 2010; Maleki et al., 2017; Mauri et al., 2016; Matos et al., 2019). In South Africa, for example, the electric water heaters (EWH) in multiple cities were retrofitted with control systems by Roux et al. (2018), allowing the energy provider to switch off the EWHs during peak hours to reduce the stress on the supply by means of direct control. Different forms of centralised EWH control have been proposed, with three key control objectives, namely, cumulative energy usage reduction, efficiently managing the load, and user comfort (Roux et al., 2018; Kepplinger et al., 2019). Direct control provides the benefit of being able to reduce the strain on the grid during high demand periods, but does not take the comfort of the user into account. Combining the benefits of EWH management and load-matched solar PV generation in a school environment can potentially provide large reductions in monthly demand charges by reducing a school's peak power demand while maintaining user comfort (Hohne et al., 2019). This will also provide the opportunity to divert excess generated solar energy to be stored in the EWH, reducing the potential grid load used by the EWHs and maximising all three control objectives.

Between 2011 and 2017 there were several investigations into the implementation of energy-saving techniques within a school environment. These studies and their relevant results are discussed below.

A recent study by Gallego Sanchez Torija et al. (2017) considered the incorporation of water usage in energy audits within a school environment in Spain. The objective of the research was to measure the water usage and potential emissions per user within the school building, as well as the potential improvement due to a series of proposals aimed at reducing water usage while maintaining user comfort. The study provides a usage cost breakdown with payback times for the various interventions.

Hida et al. (2010) determined the optimal PV solar system size to reduce the total CO_2 emissions while maximising cost savings within medium- and large commercial installations. The paper does consider the load profiles of commercial buildings, but only to see the effect of various solar installations using linear programming techniques. No methods are implemented to shift or alter the load profile using EWH or battery storage to better suit the solar PV system's generation capacity.

A school in Tanzania was evaluated by Mauri et al. (2016), and proposed a solution by which fuzzy logic is applied to learning algorithms to forecast a schools daily load depending on a variety of factors. The school is situated in a rural, off-grid area within the Arusha Region of the country with limited energy generation and storage capabilities. The research focuses on optimising the school's power delivery systems to match the forecasted load. The paper states that each day of the week will have the same load profile as the previous weeks, and although holidays are considered, the forecasts assume that there are no seasonal changes in load patterns. Also, similar to the previously discussed study, the entire load profile of the building is taken into account without any measures put in place to schedule EWH elements in order to shift the schools load profile.

Maleki et al. (2017) present a simplified method for optimal sizing of renewable energy hybrid systems for schools. During their research various field studies were conducted to gain an understanding of school building layouts and energy usages. From this information, a series of equations were created relating to school population and building size, capable of determining the optimal energy system size without the need for intensive simulations techniques. A drawback to the technique used is the homogeneous nature of South

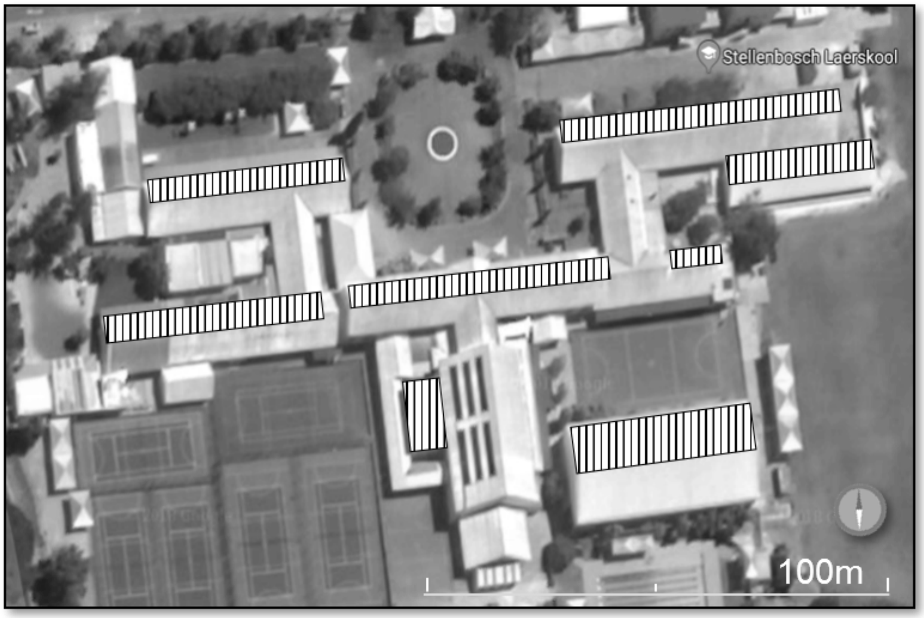


Figure 1: Satellite image of school evaluated with suitable roof area for PV installation highlighted, (Google maps).

Korean schools. Information presented in the study confirmed that most of the classrooms were similarly sized and seated a similar number of students, far different from the education standards in a developing country such as South Africa.

Although various energy-saving techniques within a school environment have been proposed (Hida et al., 2010; Mauri et al., 2016; Maleki et al., 2017; Gallego Sanchez Torija et al., 2017), none of the solutions present a demand-limiter through intelligent EWH control, crucial for reducing demand charges at institutions billed on a demand-based tariff structure, combined with an optimally sized solar system for maximal utility bill reduction. Many of the proposed solutions were created for developed countries, unlike South Africa, where effectively managing the available energy supply is essential. Additionally, none of the existing interventions implement user-specific EWH control schemes using real-time usage data to maximise utility bill and carbon emission savings while maintaining user comfort.

In this paper, we assess the use of a grid-tied PV solution in combination with load shifting through smart scheduling of energy-storing electric water heaters to reduce both energy usage from the grid (and resultant CO_2 emissions), peak load, and the electricity bill of a school in South Africa, while ensuring the hot water demand is met. Three approaches are compared with the normally used “always on” thermostat control – all three use excess solar dumping to augment supply and a centralised demand-drive priority water heating. The three incremental approaches are (1) with a single target-temperature thermostat and modulated schedule employed, (2) with a bi-thermostat and modulated schedule employed, and (3) a demand-limiting controller with the bi-thermostat. The first two aim to manage the total energy through schedule control, while the third manages the peak demand. Crucially, the evaluated school is billed for basic energy used and monthly peak power demand, as opposed to a flat energy rate or time of use rate. The school is shown in Figure 1 with the highlighted sections illustrating the suitable roof installation area to achieve optimal PV generation.

2. Proposed EWH heating prioritisation algorithm

This section describes the intelligent water heater control schemes that are evaluated in combination with an optimally sized solar PV installation to minimise the utility bills of the evaluated school. A feature table highlighting the capabilities of each evaluated configuration is presented in Table 1.

To determine the consumption profiles for each EWH and to establish when hot water would be needed, the measured hot water usage was analysed for each month, and a probability of hot water use was calculated for

Table 1: Feature table of evaluated interventions

Energy saving intervention	**Prioritised heating**	**Excess solar dumping**	**Schedule Control**	**Bi-thermostat**	**μGrid demand limiting**
Thermostat-control	✗	✗	✗	✗	✗
Smart-schedule control and solar PV	✓	✓	✓	✗	✗
Bi-thermal control and solar PV	✓	✓	✓	✓	✗
Demand-limiting control and solar PV	✓	✓	✗	✓	✓

each half hour of each day of the week. An iterative process was then followed to remove outlier consumption events by applying a threshold to the probabilities.

2.1. Prioritised heating

The principal priority control is included in all three evaluated interventions, and calculates the urgency with which each EWH needs to be heated using a cost function similar to the one proposed by Roux et al. (2018). The cost function is based on two key factors: (1) the time until the next expected water usage event, and (2) time required to heat the water from its real-time measured temperature to a target internal temperature, T_{set}. Assuming both factors carry the same weight the cost function can be defined as:

$$k_n = t_{\text{heat}} - t_{\text{event}} \tag{1}$$

The cost function is calculated each simulated minute for every EWH, n, where t_{event} is the time before the next expected usage and t_{heat} is the required heating time from the present EWH outlet temperature to the target temperature T_{set}. The time before the next expected usage is based on historical usage patterns with margins for error, and the time to heat the EWH is determined by its measured internal temperature, volume and element rating. Only the EWHs with highest priority, k_n, are heated such that a minimal amount of energy is used while maintaining user comfort and limiting the power draw of the EWH elements depending on the selected peak power demand manager control configuration.

2.2. Excess solar dumping

All three evaluated interventions make use of the excess energy from the solar supply to augment water heating. The mechanism uses the priority list to assign water heaters to excess solar supply, but only as much as is available and based on the prioritised water heaters' element rating. For example, if 5 kW were available, and the top three water heaters in decreasing priority had respective element ratings of 3 kW, 3 kW and 2 kW, the simulation algorithm would use solar power to heat the former and the latter. Grid power would be used for the middle one, but only if the chosen smart controller allows for 3 kW grid draw at the time.

2.3. Smart Schedule + PV

The first energy-saving intervention uses a smart schedule that overrides the prioritisation control to only heat for a set time before hot water use to reduce standing losses. This methods uses only a single target temperature on the thermostat, namely 70 °C, as would be the case on a normal water heater. The schedule has to balance the need to limit the standing losses of the water heater and the need to deliver hot water when needed, while dumping the excess energy from the solar supply into the EWHs. Unless solar power is available, the scheduler will only allow turning the element on if the time until the next event, t_{event}, is less than three hours. The three hour heating period was selected after repeated simulations, resulting in the least number of cold water usage events per kWh used.

2.4. Smart schedule + PV + bi-thermostat

The second energy-saving intervention, based on the first, introduces a bi-thermal heating mechanism (BiTherm + PV). For this approach, the EWHs are heated to different target temperatures, T_{set}, for grid- and solar heating, allowing solar energy to be diverted to the EWHs if excess solar is available, even if the water temperature is higher than the grid target temperature. The bi-thermostat heats to a target temperature of 50 °C for grid heating and 90 °C for excess solar heating. By employing a higher target temperature for

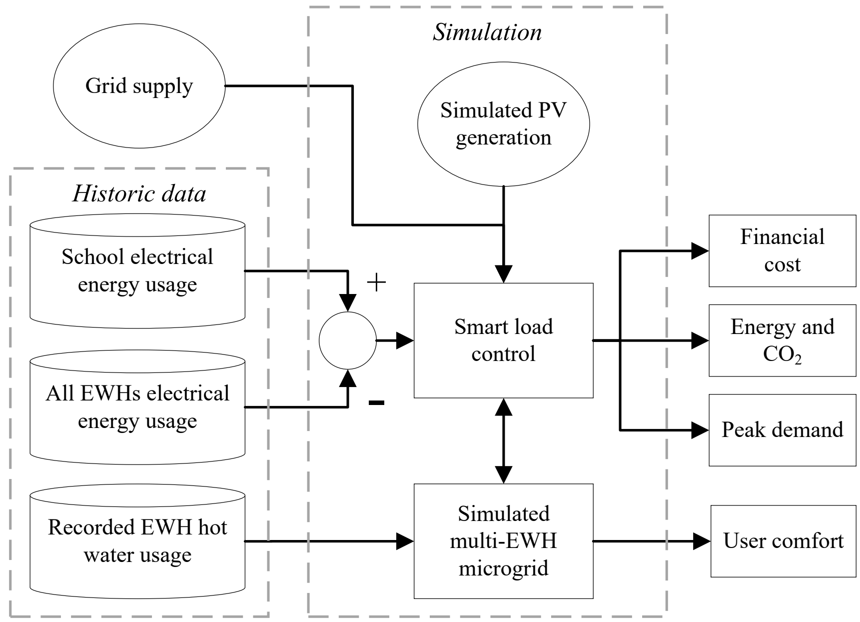


Figure 2: Simplified diagram of simulation setup.

solar heating, the EWHs will remain suitably hot for usage for longer periods before needing to use energy from the grid. In addition to increasing the target temperature for solar heating, the temperature difference between the levels can be increased by lowering the heating temperature T_{set} for grid heating. A suitable temperature delta is determined by maximising cost savings while maintaining user comfort. It should be noted that the bi-thermal control scheme includes all the features of the prioritisation scheduler, in addition to having heating thresholds as shown in the feature table, Table 1. The specific thresholds are defined in the parameter table, Table 2.

2.5. Demand-limiting + PV + bi-thermostat

The final control scheme is a demand-limited heating method in conjunction with the bi-thermal heating mechanism (BiTherm + DemLim + PV), which controls the EWHs such that the buildings' peak monthly power demand is not affected by the water heaters. This would imply that EWH heating does not contribute to any of the school's peak demand charges. The algorithm retrieves historical- and current building energy usage data, comparing the current power usage to the recorded maximum. The EWHs are then heated according to priority without exceeding a calculated power limit in order to not increase the recorded peak monthly demand. Since the intention of this scheme was to perform demand limiting, the three hours limitation was removed, allowing the EWHs to be heated to their target temperatures and remain hot enough during peak-demand times to minimise the number of cold events at the cost of increased standing losses.

3. Experimental setup

This section expands on the experimental setup, consisting of validated EWH and solar PV generation models. We also explain how the performance of the simulation results are evaluated for the various interventions and control schemes. A simplified diagram of the simulation setup is presented in Figure 2.

3.1. Simulation Setup

The simulation uses measured energy- and hot water usage data from the school over a 12-month period, and implements a validated thermal EWH model and solar PV generation model for water heater and solar

PV generation modelling respectively (Roux et al., 2018; Booysen and Cloete, 2016). The evaluated building was selected due to having measured energy- and EWH usage data allowing for more accurate modelling for all seasons. The full dataset is available at `http://bit.ly/bithermostat`.

3.1.1. Solar PV Simulation

The solar PV generation modelling is performed using SAM (System Advisor Model) open-source libraries that employ a photo-voltaic performance model developed by NREL (2018), and calculates the AC electrical output for each hour over a one year period. The model gathers solar resource and temperature data from a weather file obtained using the European Commission's photo-voltaic geographical information system for a specified location (PVGIS, 2018). The specific module sub-model implementation is an improvement to the five parameter model originally defined by De Soto et al. (2004), and uses a six-parameter single-diode model by the California energy commission (CEC) (NREL, 2018). SAM's inverter model is an implementation of an empirical model described by King et al. (2007), which uses manufacturer specifications with empirically derived coefficients to simulate the AC output power for a specific DC input (NREL, 2018).

The input parameters required for the simulation is the maximum power voltage, maximum power current, open circuit voltage and short circuit voltage per panel. For the inverter the maximum AC output power, maximum DC input power and nominal operating ranges are required. The parameters and their respective values are listed in Table 2. The number of modules chosen during simulation was selected based on the schools energy usage and peak-demand profile obtained from the school's energy usage database containing hourly smart meter telemetry from 1 June 2017 until 31 May 2018.

3.1.2. EWH Simulation

The building's EWH water consumption and energy usage was captured with smart water heater controllers that were retrofitted to all seven EWHs installed within the school, and simulated for the three intelligent water heater configurations discussed in Section 2. Since all the EWHs are mounted horizontally, the norm in South Africa, the EWHs are modelled using the computationally efficient two-node model proposed by Nel et al. (2018).

The two-node model accounts for stratification, whereby less dense, warm water rises above the cold water and separates the two masses by a thermocline. The temperature of the separate masses are governed by two differential equations effectively acting as two separate single nodes. The recorded internal temperature of the EWH was selected from the upper, outlet node. The parameters required to model an EWH are: the orientation, tank volume, element power rating, and thermal resistance. To execute the model, the following measurements are required for each sample period (chosen as 1 minute): volume water used, inlet water temperature, and ambient temperature. Using these parameters the model estimates electrical energy used, energy lost to the environment (standing losses) and thermal energy used (the hot water leaving the tank) (Nel et al., 2018).

The EWH model is used with two heating control schemes for comparison, *thermostat* control and priority-driven *smart-schedule* control. Under *thermostat* control, a thermostat measures the internal water temperature and regulates the heating element to maintain a target temperature T_{set}. *Thermostat* control does not take demand into account, and while user-comfort may be maintained through best-effort heating, as much as 20% of the used energy is lost through the heater surface as standing losses (Nel et al., 2018). A suitable level of user-comfort was selected as fewer than one of every one hundred usage events being a cold-event.

The three control schemes are simulated for the entire 365 day period, using simulation time steps of 1 minute. The evaluated output includes the energy used, peak power consumption, cold event count and mean event temperature for each EWH.

3.1.3. Cost Estimation

The assessed building is subject to a demand-based tariff structure by which the school is charged for basic energy used, as well as the peak monthly power demand, which is sampled and returned every 30 minutes (Stellenbosch Municipality, 2018; Eskom, 2018). As such, the simulation setup's primary goal is to not only reduce the building's total grid energy consumption and CO_2 emissions, but its peak power demand as well. By optimally sizing the solar array and selecting a suitable intelligent water heater control scheme, maximal cost savings will be achieved for the amount invested. The cost estimation is performed by calculating the utility bill reduction for each energy-saving configuration compared to the baseline, and determining a basic

Table 2: Parameters used during experimental setup

Parameters	Value	Unit
School data		
Students and staff	1052	Persons
Classrooms	34	Rooms
EWH modelling		
Number of EWHs	7	-
Element power	3x2kW,4x3kW	kW
Thermal resistance (Booysen and Cloete, 2016)	0.46	°C/W
Thermostat hysteresis (Booysen and Cloete, 2016)	7.4	%
Target temperature, T_{set} for grid heating	50,70	°C
Target temperature, T_{set} for solar heating	90	°C
Cold event threshold, $T_{threshold}$ (Jacobs et al., 2018)	40	°C
PV modules		
Maximum power	320	W
Maximum power voltage	37.5	V
Maximum power current	8.53	A
Open circuit voltage	46	V
Open circuit current	9.5	A
Suitable PV installation area	2180	m^2
PV tilt angle	27.8	degrees
Azimuth	350	degrees
Number evaluated (selected)	80–220 (110)	-
Inverter		
Maximum AC output power	36	kW
Maximum DC input power	40.8	kW
Efficiency	98.6	%

payback period to investigate the validity of the simulated intervention. Table 2 lists the parameters used during the simulation.

3.2. Evaluation and metrics

The complete system is evaluated by comparing the utility bill reduction, basic energy- and peak-demand savings, user-comfort, and carbon emission savings for the different energy-saving interventions compared to the school's baseline usage throughout the evaluated period. The baseline usage of the school is defined as the total energy usage without a solar system installed, with all installed EWHs employing thermostat heating control with a target temperature of 70°C. The performance of the three intelligent water heater control schemes is measured in terms of total basic energy usage, reduction in peak monthly power demand and user comfort. The solar PV generation optimisation methods performance is evaluated by the peak power demand reduction, total grid energy saved and reduction in carbon emissions. A potential return on investment (ROI) period is calculated for the school with solar and smart scheduling using available balance of system (BOS) and labour cost estimates (International, Renewable Energy Agency, 2016).

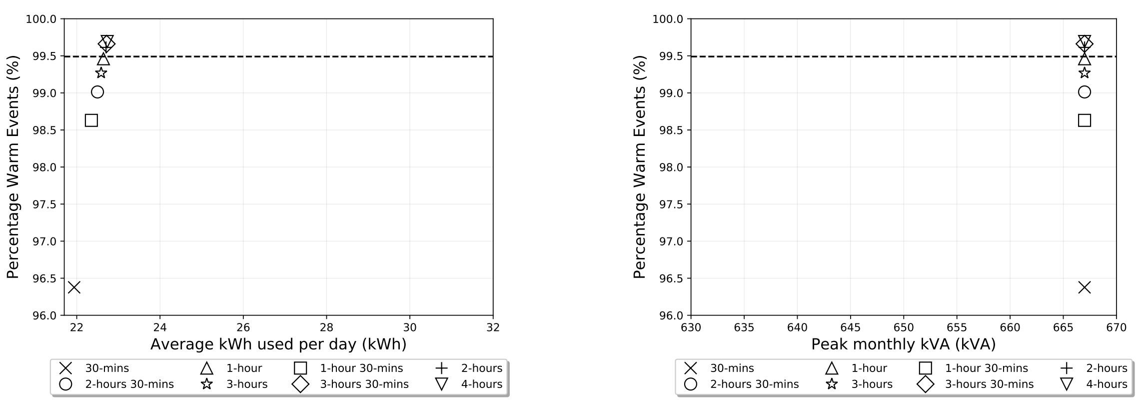
4. Results and discussion

This section details the results obtained using the simulation setup and parameters discussed.
The baseline energy cost for the school without any intervention was R292 176 ($20 971) for 157 MWh used during the evaluation period, generating an estimated 117 tons of CO_2 emissions. For the solar PV simulations an array size of 110 modules with an installed capacity of 35.2 kWp was chosen, providing the greatest cost to benefit ratio while fully utilising the inverter capacity. The installed cost of the solar system is estimated to be R453 500 ($30 750), and reduced the school's yearly energy cost by 24% to an estimated R220 950 ($15 859) without any intelligent water heater scheduling.

Additional improvements in utility bill reduction from EWH scheduling were as follows. With the solar system and EWH prioritisation scheduler the yearly energy cost was lowered to R216 757 ($15 558). By implementing the second EWH control scheme using a bi-thermal heating threshold of 50°C from grid heating and 90°C from solar heating the utility cost was R210 288 ($15 093). A temperature delta of 40°C was selected after multiple simulations and determined to be the most cost effective, without negatively impacting user comfort. Finally, when using the demand-limiter control scheme by limiting the maximum power usage of the EWHs the demand-charge savings reduced the utility cost to R204 400 (\$14 671) for the year, a reduction of more than 30% compared to the school's baseline, reducing the estimated yearly carbon emissions to 78 tons of CO_2 per year while maintaining user comfort.

This allowed for additional yearly savings of R16 550 (\$1 188) through the use of intelligent water heater scheduling while minimising "lost" solar energy and reducing the demand of the school and local municipality while maximising warm usage events. A warm usage event is defined as an event with a water temperature above 40°C, therefore, all usage events that are not cold events are defined as warm usage events. Additional results comparing the simulated energy saving interventions with the school's baseline can be found in Table 3.

Figures 3a and 3b show the average daily kWh grid-usage and total peak kVA for the year for the second simulated intervention, the bi-thermal heating mechanism with a prioritisation scheduler and solar power system (BiTherm + PV). The plotted results show the usages for various scheduling periods t_{event}. A longer scheduling period results in larger standing losses as the EWHs are heated earlier, and reduces the number of cold events by allowing the heater elements to be switched on for a longer period. From Figure 3b it is seen that the maximum monthly kVA usages for the year, defined as the sum of the building's peak monthly demand throughout the evaluation period, remain the same for all scheduling periods. This is due to the water heaters being scheduled to heat for the first usages very early in the morning. By the time the peak-demand period arrives late morning during winter months or early afternoon during summer months the water has already been heated to a suitable temperature regardless of the scheduling period. From the results the cold event percentages reached a steady state for scheduling periods of greater than 3 hours, and was selected as the optimal scheduling period providing maximal user comfort for the energy used. The dashed line represents the warm event percentage of the thermostat or baseline EWH control scheme. The increased user comfort compared to thermostat control for scheduling periods greater than 3 hours can be attributed to the higher EWH target temperature of 90°C for solar heating. This allows the water to remain at a suitable temperature for late evening and early morning usages while allowing the heating elements enough time to heat the water from the grid to be at the required target temperature for peak usage times.



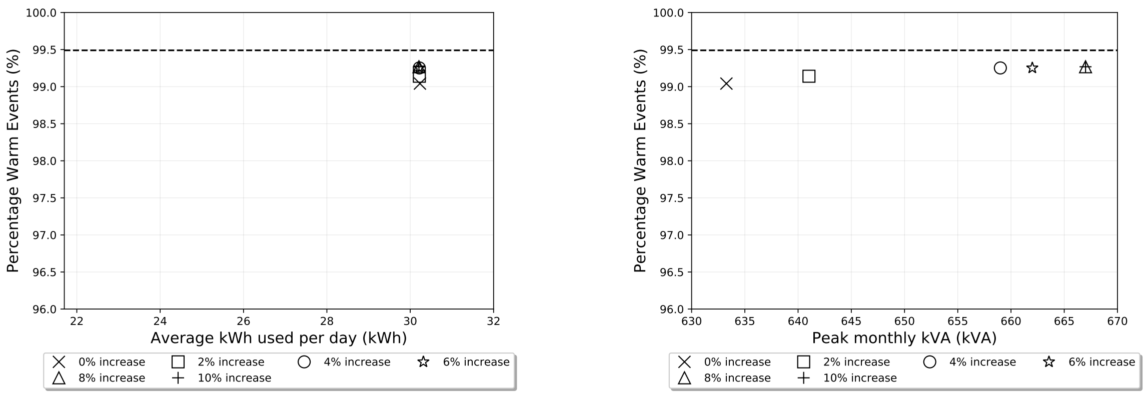
(a) kWh used from grid

(b) Peak monthly kVA for the year

Figure 3: Usage results for the (BiTherm + PV) intervention

Figures 4a and 4b present the average daily kWh grid-usage and maximum monthly kVA for the year for solar intervention with a bi-thermal threshold as well as limiting the demand of the EWHs (BiTherm + DemLim + PV). The plotted results show the usages as the demand limit is raised. A higher demand limit increases the peak monthly kVA for the year while reducing cold events by allowing more EWHs to be heated simultaneously. The large increase in kWh usage compared to the (BiTherm + PV) intervention is due to the 3 hour scheduling period, t_{event}, being removed. As a result, the EWHs enter a thermostat control state, ensuring that the water heaters are always above the minimum threshold temperature of 40 °C without taking the estimated time before the next water usage event into account. This was done to allow the water sufficient time to heat, as no EWH elements are allowed to be active during the demand-limited period with a 0% increase in peak monthly demand.

From the maximum monthly kVA graph the cold events for the 4% and 6% as well as the 8% and 10% increases are exactly the same. It should be noted that this is due to the percentage increase in allowable demand not being greater than the EWH element rating of (2kW and 3kW). From the results a demand-limiter with 0% demand increase was selected as a result of providing the greatest demand-charge savings while maintaining a suitable level of user comfort.



(a) kWh used from grid (b) Peak monthly kVA for the year

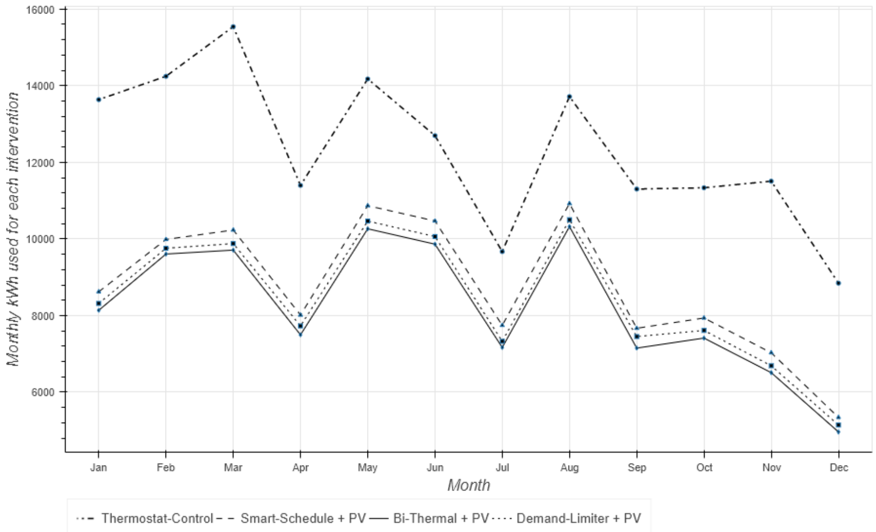
Figure 4: Usage results for the (BiTherm + DemLim + PV) intervention

Figures 5a and 5b present the kWh used and the peak monthly power demand for each intervention for each month of the year. From the graphs it is apparent that all three interventions provide a noticeable improvement compared to the measured baseline. From the kWh per month graph the slight increase in energy usage by the (BiTherm + DemLim + PV) control scheme compared to the (BiTherm + PV) configuration is visible, but it is clear that the introduction of bi-thermal temperature thresholds allowed for a sizeable reduction in energy usage compared to the Smart Schedule and PV control scheme.

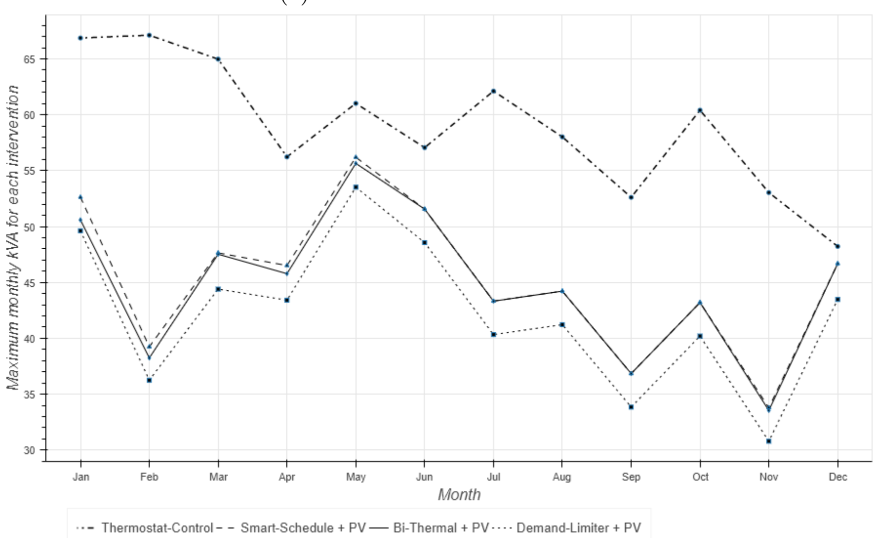
The peak demand savings graph shows large improvements for the simulated interventions when compared to the building's baseline. The relatively small improvements during the winter months can be attributed to the fact the the school's monthly peak demand occurs earlier in the morning when solar PV generation is minimal. During the summer months the school's energy usage profile is better suited for solar intervention, with the peak monthly demand occurring early afternoon when solar PV generation is at its highest. Moreover, from the graph the improvements seen from the demand limited control scheme (BiTherm + DemLim + PV) is clearly visible compared to the other two simulated configurations. This resulted in the largest cost savings, reducing the school's monthly energy bill by an average of 30% per month, with an estimated basic payback period of six and a half years.

An improvement to the demand-limiting approach presented in this study is to employ optimal battery sizing methods to achieve further demand reduction, reducing the peak power usage during the early mornings, particularly during winter months while further reducing potential lost solar energy. This should be done while remaining cost effective through large demand-charge savings.

Since there may be schools that pay a flat fee for energy, we also simulated the scenarios for a fixed cost per kWh used of 1.6727 R/kWh and a basic charge of R273.96 per month for an 80A one- or three-phase line. For the same period analysed above (1 June 2017 to 31 May 2018), the flat-fee cost was R266 443 for thermostat control, R185 947 for Solar& prioritisation scheduling (a saving of 30.21%), and R175 911 for the Solar & bi-thermostat (a saving of 34%).



(a) kWh used for each month



(b) Peak monthly kVA for each month

Figure 5: Usage results for the evaluated interventions

Table 3: Simulation results for evaluated school for the period 1 June 2017 to 31 May 2018

Parameter	**School baseline**	**Solar & prioritisation scheduling**	**Solar & bi-thermostat**	**Solar & demand-limited EWHs**	**Unit**
Total energy usage	157.3	109.2	103.2	105.3	MWh
Daily energy usage [min,mean,max]	[127,430,771]	[79,299,563]	[75,283,517]	[76,289,529]	kWh
Daily max kVA [min,median,max]	[8,37,72]	[0,30,55]	[0,30,54]	[0,28,53]	kVA
Warm event percentage	99.49	99.24	99.48	99.03	%
Yearly CO_2 Emissions	117 065	81 274	76 807	78 366	kg
Average utility bill saving	0	25.81	28.02	30.05	%

5. Conclusion

To date, no other published literature has assessed the benefits of effectively managing electric water heaters combined with a solar power system to reduce the utility bills and carbon emissions within a school environment, and raises important questions regarding the applicability of the simulated system for other schools with larger energy- and water usage footprints. Research done during this study has shown there to be limitations with the methods used regarding data collection using physical devices installed within the school and performing the study at a single school. Because of these limitations, more research should be done by implementing the interventions in a larger number of schools to provide more conclusive results. From the results obtained through simulation, it is evident that the reduction of the cost of energy used is viable for the evaluated school. By designing an optimal solar power system it was found that the school's grid usage and peak monthly power demand was reduced significantly, with a 24% reduction in monthly energy costs and minimal excess solar energy lost. Three control schemes of intelligent water heater scheduling were researched. Firstly, a priority based scheduler was configured to heat water using the school's water usage history, while diverting any excess solar energy to the water heaters to exploit their energy storage capabilities, further increasing the school's energy bill savings to 26% per month. Secondly, a bi-thermal control method was added to the priority based scheduler, employing a temperature delta to increase the amount of solar energy to be stored within the water heater tank while minimising their grid reliance and improving the monthly savings to 28% per month. Finally, a demand-limiter control scheme was implemented in conjunction with bi-thermal control resulting in large demand-charge savings and an average energy bill reduction of 30% per month, producing the maximum savings while maintaining suitable levels of user comfort. Therefore, with the above interventions, the 30% utility savings can be used to improve the quality of education delivered by the school without placing further pressure on the budget.

Acknowledgements

The authors thank the Water Research Commission (WRC) for funding of the water heater project through grant K1-7163, MTN South Africa for financial support through grant S003061, and Scatec Solar for their financial support through the Scatec Solar Chair.

References

Baker, L., Sovacool, B.K., 2017. The political economy of technological capabilities and global production networks in south africa's wind and solar photovoltaic (pv) industries. Political Geography 60, 1 – 12. doi:10.1016/j.polgeo.2017.03.003.

Booysen, M.J., Cloete, A.H., 2016. Sustainability through intelligent scheduling of electric water heaters in a smart grid, in: 2016 IEEE 2nd Intl Conf on Big Data Intelligence and Computing and Cyber Science and Technology Congress, pp. 848–855. doi:10.1109/DASC-PICom-DataCom-CyberSciTec.2016.145.

Chudy, M., Mwaura, J., Walwyn, D., Lalk, J., 2015. The effect of increased photovoltaic energy generation on electricity price and capacity in south africa, in: AFRICON 2015, pp. 1–6. doi:10.1109/AFRCON.2015.7331968.

COGTA, 2017. Cooperative Governance and Traditional Affairs (South Africa) Presentation - NERSA, Bloemfontein. http://www.nersa.org.za/Admin/Document/Editor/file/Consultations/Electricity/Presentations/COGTA% 15%20Nov.pdf.

De Soto, W., Klein, S., Beckman, W., 2004. Improvement and validation of a model for photovoltaic array performance. Solar Energy 80, 78–88.

Deloitte, 2017. An overview of electricity consumption and pricing in south africa. http://www.eskom.co.za/Documents/EcoOverviewElectricitySA-2017.pdf. Accessed on 2018-07-15.

Department of Energy, S.A., 2018. Coal resources overview. http://www.energy.gov.za/files/coal_frame.html. Accessed on 2018-08-22.

Energy Administration, U.S., 2016. International energy outlook 2016. https://www.eia.gov/outlooks/ieo/pdf/0484(2016).pdf. Accessed on 2018-07-12.

Eskom, 2018. Eskom yearly integrated report for the year 2017. http://www.eskom.co.za/IR2017/Documents/Eskom_integrated_report_2017.pdf. Accessed on 2018-07-15.

Gallego Sanchez Torija, J., Larrumbide, E., Bedoya, C., 2017. The incorporation of the study into water consumption in energy audits in schools. Revista de la construccin 16, 361–373.

Hida, Y., Ito, Y., Yokoyama, R., Iba, K., 2010. The effect of increased photovoltaic energy generation on electricity price and capacity in south africa, in: 45th International Universities Power Engineering Conference UPEC2010, pp. 1–5.

Hirth, L., 2015. Market value of solar power: Is photovoltaics cost-competitive? IET Renewable Power Generation 9, 37–45. doi:10.1049/iet-rpg.2014.0101.

Hohne, P., Kusakana, K., Numbi, B., 2019. A review of water heating technologies: An application to the South African context. Energy Reports 5, 1 – 19. doi:10.1016/j.egyr.2018.10.013.

International, Renewable Energy Agency, 2016. Solar PV in Africa: Costs and markets. https://www.irena.org/DocumentDownloads/Publications/IRENA_Solar_PV_Costs_Africa_2016.pdf. Accessed on 2018-07-26.

IoL, 2018. Eskoms monopoly plunging sa into power shortages. https://www.iol.co.za/news/politics/eskoms-monopoly-plunging-sa-into-power-shortages-says-da-18178900. Accessed on 2018-12-03.

Jacobs, H., Botha, B., Blokker, M., 2018. Household Hot Water Temperature An Analysis at End-Use Level, in: International WDSA / CCWI 2018 Joint Conference, Kingston, Ontario, Canada July 23-25, pp. 1–14.

Kepplinger, P., Huber, G., Preißinger, M., Petrasch, J., 2019. State estimation of resistive domestic hot water heaters in arbitrary operation modes for demand side management. Thermal Science and Engineering Progress 9, 94 – 109. doi:10.1016/j.tsep.2018.11.003.

King, D., Gonzalez, S., Galbraith, G., Boyson, W., 2007. Performance model for grid-connected photovoltaic inverters. Sandia National Laboratories 2007 50, 44.

Maleki, A., Rosen, M.A., Pourfayaz, F., 2017. Optimal Operation of a Grid-Connected Hybrid Renewable Energy System for Residential Applications. Sustainability 9, 1–20.

Matos, C., Bentes, I., Pereira, S., Faria, D., Briga-Sa, A., 2019. Energy consumption, co2 emissions and costs related to baths water consumption depending on the temperature and the use of flow reducing valves. Science of The Total Environment 646, 280 – 289. doi:10.1016/j.scitotenv.2018.07.290.

Mauri, M., Carmeli, M.S., Merlo, M., Brivio, C., Mbuya, M., 2016. Neural network based load forecasting and fuzzy logic ems for ngarenanyuki school microgrid, in: 2016 International Symposium on Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM), pp. 321–326.

National Treasury, S.A., 2018. Goverment spending plans extract from 2017 budget review. http://www.treasury.gov.za/documents/national%20budget/2017/review/BR4.%20Spending%20plans.pdf. Accessed on 2018-07-16.

Nel, P.J.C., Booysen, M.J., van der Merwe, B., 2018. A computationally inexpensive energy model for horizontal electric water heaters with scheduling. IEEE Transactions on Smart Grid 9, 48–56. doi:10.1109/TSG.2016.2544882.

NREL, 2018. Solar advisor model technical reference. https://www.nrel.gov/docs/fy15osti/64102.pdf. Accessed on 2018-08-22.

Osuri, S.O., Ngoma, J.L., Chowdhury, S.P., 2015. Cost-effective renewable energy technologies in universities of south africa: A case study, in: International Conference on Renewable Power Generation (RPG 2015), pp. 1–5.

PVGIS, E.C., 2018. Photovoltaic geographical information system. http://re.jrc.ec.europa.eu/pvg_tools/en/tools.html#TMY. Accessed on 2018-07-12.

Roux, M., Apperley, M., Booysen, M., 2018. Comfort, peak load and energy: Centralised control of water heaters for demand-driven prioritisation. Energy for Sustainable Development 44, 78 – 86. doi:10.1016/j.esd.2018.03.006.

Sedibe, M., 2011. Inequality of access to resources in previously disadvantaged south african high schools. Journal of Social Sciences 28, 129–135. doi:10.1080/09718923.2011.11892937.

Smit, S., Musango, J.K., Brent, A.C., 2019. Understanding electricity legitimacy dynamics in an urban informal settlement in south africa: A community based system dynamics approach. Energy for Sustainable Development 49, 39 – 52. doi:10.1016/j.esd.2019.01.004.

Stellenbosch Municipality, 2018. Stellenbosch Municipality 2017/2018 tariffs. https://www.stellenbosch.gov.za/documents/idp-budget/2017-2018-idp-budget/draft-budget-2017-2018/4610-final-tariffs-2017-2018/file. Accessed on 2018-07-23.