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Optimal Sizing of Solar Home Systems: Charge Controller Technology and Its Influence on System Design

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HIGHLIGHTS

- Optimal Solar Home System sizing based on multi-objective optimization
- Influence of charge controller technology on system sizing and life cycle costs
- Maximum Power Point Tracker achieves cost savings of 4.0 % to 8.6 %
- Results show high robustness regarding irradiance, load profile, and economic variation

ABSTRACT

Solar Home Systems are a promising solution to enable access to affordable, reliable, sustainable, and modern energy for non-electrified areas, especially in the Global South. In this study, the influence of the charge controller technologies Maximum Point Tracker (MPPT) and Pulse Width Modulation (PWM) on the optimal system design and system performance is analyzed. Therefore, a multi-objective optimization that minimizes the number of days with Power-Cut-Offs and the Levelized Cost of Electricity for three Solar Home System sizes and three sub-saharan locations is conducted. Cost savings of the MPPT controller are in the range of 4.0 % to 8.6 % compared to the PWM controller. This is achieved by a reduction of the optimal installed photovoltaic peak power by 31.2 % to 38.6 % and the battery capacity by 2.8 % to 8.8 %. A sensitivity analysis shows the high robustness of cost savings regarding a variation in solar irradiance, load profile, and charge controller investment costs. Therefore, MPPT charge controllers are a promising solution even for the smallest Solar Home System sizes to reduce system costs compared to PWM controllers. The applied numerical simulation tool is open-source to enhance openness and transparency in modeling studies.

KEYWORDS

- Solar Home Systems
- System sizing
- Multi-objective optimization
- Charge controller technology
- Open-source simulation tool

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NOMENCLATURE

Introduction	
SHS	Solar Home Systems
PWM	Pulse Width Modulation
MPPT	Maximum Power Point Tracker
PCO	Power-Cut-Offs
LCoE	Levelized Cost of Electricity
Methodology – Photovoltaic model	
PV	Photovoltaic
DC	Direct current
I	Photovoltaic current [A]
I_L	Photovoltaic light current [A]
I_D	Photovoltaic diode current [A]
I_{sh}	Photovoltaic shunt current [A]
I_0	Photovoltaic diode reverse saturation current [A]
V	Photovoltaic voltage [V]
R_s	Photovoltaic series resistance [Ω]
R_{sh}	Photovoltaic shunt resistance [Ω]
a	Photovoltaic modified ideality factor
N_s	Photovoltaic number of cells in series
n_i	Photovoltaic usual ideality factor
k	Boltzmann's constant
q	Electron charge
T_c	Photovoltaic cell temperature [K]
$P_{PWM, PV}$	Photovoltaic output power with PWM controller [W]
$V_{battery}$	Battery voltage [V]
$P_{MPPT, PV}$	Photovoltaic output power with MPPT controller [W]
G_{poa}	Total plane of array irradiance [$W \cdot m^{-2}$]
G_{STC}	Solar irradiance at Standard Test Conditions [$W \cdot m^{-2}$]
P_{dc0}	Photovoltaic peak output power [Wp]
γ_{pdco}	Photovoltaic temperature coefficient of P_{dc0} [$1 \cdot K^{-1}$]
T_{cell}	Photovoltaic cell temperature [K]
T_{STC}	Temperature at Standard Test Conditions [K]
V_{wind}	Wind speed [$m \cdot s^{-1}$]
T_a	Ambient temperature [K]
Methodology – Power Component model	
P_{out}	Power component output power [W]
η	Power component efficiency
p_{self}	Power component parameter referred to non-performance-related self-consumption
V_{loss}	Power component parameter referred to voltage losses over diodes and transistors
r_{loss}	Power component parameter referred to ohmic losses
P_{in}	Power component input power [W]
Methodology – Battery model	
η_{CH}	Battery charge efficiency
η_{DCH}	Battery discharge efficiency
SoC	Battery state of charge
SoC _{cut off, CH}	Battery state of charge end of charge boundary
SoC _{cut off, DCH}	Battery state of charge end of discharge boundary
V_{CH}	Battery voltage during charge [V]
V_{DCH}	Battery voltage during discharge [V]
P_T	Battery terminal power [W]
$P_{loss, total}$	Battery charge and discharge losses [W]
$P_{self-discharge}$	Battery self-discharge power [W]
dt	Simulation timestep [h]
E_{actual}	Battery capacity at simulation timestep [Wh]
T_b	Battery cell temperature [K]
h	Battery heat transfer coefficient [$W \cdot m^{-2} \cdot K^{-1}$]
A	Battery surface-specific energy [$Wh \cdot m^{-2}$]
m	Battery mass-specific energy [$Wh \cdot kg^{-1}$]
c_p	Battery average heat capacity [$J \cdot kg^{-1} \cdot K^{-1}$]
cycle life	Battery cycle life
DoD	Battery depth of discharge

cycle life _{micro-cycle}	Battery cycle life of micro-cycle
DOD	Battery mean depth of discharge of micro-cycle
C _{relative loss, micro-cycle}	Battery relative capacity degradation of micro-cycle
E _{micro-cycle}	Energy cycled during a battery micro-cycle [Wh]
C _{nominal}	Battery nominal capacity [Wh]
C _{end of life}	Battery end of life capacity [Wh]
C _{loss, micro-cycle}	Battery absolute capacity degradation of micro-cycle due to cycling aging [Wh]
calendric life	Battery float lifetime [a]
C _{loss, calendric}	Battery absolute capacity degradation due to calendric aging [Wh]
Methodology – Economic model	
CC	Component investment costs
OMC	Component operation and maintenance costs
BOS	Balance of System costs
ATLCC	Annual levelized cost flow [$\$/\text{a}^{-1}$]
E _{load supplied}	Supplied load energy [Wh]
A _{cc,k}	Annuity of investment costs of component k [$\$/\text{a}^{-1}$]
A _{omc,k}	Annuity of the operation and maintenance costs of component k [$\$/\text{a}^{-1}$]
A _{rc,k}	Annuity of replacement costs of component k [$\$/\text{a}^{-1}$]
A _{rv,k}	Annuity of residual costs of the component k [$\$/\text{a}^{-1}$]
CRF	Capital recovery factor
SoD _{k, t}	State of destruction of component k at the time t
i _{eff}	Annual percentage rate
HV	Hypervolume/Hyperarea
GD	Generational Distance
IGD	Inverted Generational Distance
Results	
PSH	Peak Sun Hours

1. INTRODUCTION

The Sustainable Development Goal 7 aims to ensure access to affordable, reliable, sustainable, and modern energy for the world population. In 2018 global electrification rate reached 90 % but remains lowest in sub-saharan africa with 47 %. Under current policies, it is estimated, that about 620 million people will not have access to energy in 2030, of which 85 % will be in sub-saharan africa [1]. Off-grid solar systems have a high potential to tackle this problem by improving greenhouse gas emissions, economic opportunities, private savings, health risks, and energy services compared to traditional fossil-based energy solutions [2]. They can be implemented in non-electrified rural areas and in grid-connected urban areas, which in sub-saharan africa are increasingly suffering from frequent power shortages and outages [3]. Indeed, off-grid solar systems are proving to be the leapfrog infrastructure of the current decade [4].

According to the Off-Grid Solar Market Trends Report 2020, off-grid solar household products can be categorized into *Portale Lanterns* for lighting purposes only, *Multi-light Systems* with multiple light sources and mobile charging possibilities, and *Solar Home Systems*. Solar Home Systems (SHS) are further categorized into 'Entry level' (11-20.99 Wp), 'Basic capacity' (21-49.99 Wp), 'Medium capacity' (50-99.99 Wp), and 'Higher capacity' (> 100 Wp) [5]. Lightning Global lists up-to-date SHS products, which meet their quality standard according to the IEC TS 62257-9-5:2018 [6], to set a baseline level of product quality and durability [7].

SHS normally consist of different direct current appliances, a photovoltaic panel, a charge controller, and a storage technology to buffer the fluctuating solar resource and to provide energy also during night and days with lower solar irradiation. Different battery technologies exist for usage in SHS. They differ in their technical, ecological, and economic performance [8]. Lead-acid and lithium-ion battery technologies are dominantly used in SHS applications [9]. Charles et al. state that lead-acid batteries are readily available at low cost and are the current best choice for sustainable small-scale domestic photovoltaic systems [8]. While lead-acid batteries and their lifetime prediction are examined extensively (e.g. May et al. [10], Sauer et al. [11], and Narayan et al. [12]), studies focusing on the charge controller technology and its influence on optimal system sizing and performance are rare. Charge controllers protect and control the battery charge and discharge process and specify the photovoltaic operating point with its voltage level and therewith influence the photovoltaic energy yield. Two general types of charge controller exist; Pulse Width Modulation (PWM) and Maximum Power Point Tracker (MPPT). Laguado-Serrano et al. do an experimental comparison of these two charge controller types and measure the voltage and current levels in photovoltaic and battery to determine controller efficiency. They state that PWM charge controllers have certainly a lower efficiency but are an option with a lower price in relation to the MPPT [13]. This statement is in accordance with a whitepaper by a manufacturer of off-grid solar solutions, which states that PWM charge controllers are a good low-cost solution for small systems only [14]. Müller et al. provide an analysis of MPPT charge controller design and efficiency in photovoltaic off-grid systems, including the application in SHS, and state that MPPT charge controllers offer a wider choice of photovoltaic panels even with more than 36 or 72 cells [15].

SHS sizing is a complex task due to an uncertain load profile and fluctuating solar resources. Both, over- and undersizing of a system have negative effects on system cost and reliability. Campana et al. present an open-source Visual Basic for Applications optimization tool for SHS component sizing and identify incorrectly sized systems in a case study in Namibia. Authors provide static optimal component sizing, at randomly selected performance metrics of one day of autonomy and reliability of 99.9 %. The tool further uses static component efficiency values and neglects battery degradation [16]. Rossi et al. compare the economic and environmental optimal design of grid-connected Solar Home Systems using a mixed-integer linear programming approach with an innovative cross-evaluation analysis [17]. The case-study covers an application in Italy with higher SHS capacities as introduced by [5]. Khatib et al. propose an artificial-intelligence-based standalone photovoltaic system sizing method. They use multi-objective optimization based on the objective functions loss of load probability and the life cycle costs and state that methods can successfully be used in the sizing process of such kind of systems [18]. Narayan et al. describe a genetic algorithm-based multi-objective optimization with four objectives for SHS sizing minimizing loss of load probability, excess energy, and battery size, while maximizing the battery lifetime [19]. For optimization problems involving more than three objective functions, Chen et al. propose an innovative many-objective population extremal optimization method, which outperforms state-of-the-art evolutionary algorithms tested for a DTLZ test problem [20] and other recent algorithm enhancements [21]. Mentioned sizing studies focusing on photovoltaic stand-alone systems in [18], [19] highlight that genetic algorithms are a powerful and appropriate method for the case of SHS. But there is a clear research gap in the

literature concerning studies focusing on the influence of charge controller technology on optimal SHS sizing. Further detailed open-source numerical simulation models for optimal sizing of SHS could not be identified. In this study, three SHS size categories at three locations of the main sub-saharan markets are analyzed using a state-of-the-art multi-objective genetic algorithm. The main contributions of this paper are:

1. An open-source numerical simulation tool for optimal SHS sizing is proposed that provides Pareto-optimal solutions with a minimal number of days with Power-Cut-Offs (PCO) and Levelized Cost of Electricity (LCoE).
2. The influence of charge controller technology on Pareto-optimal solutions and system sizing is analyzed.
3. A sensitivity analysis provides insight into the robustness of obtained simulation results and influencing parameters.

The methodology of this work with the developed mathematical component models, case studies analyzed, and methods applied are introduced in chapter 2. In chapter 3 the main findings of the multi-objective optimization and sensitivity analysis are presented and discussed. The authors finish the paper with conclusions on the influence of charge controller technology on SHS sizing and an outlook of future work.

2. METHODOLOGY

This section describes the mathematical and economic models for the numerical simulation. Component energy dissipation and degradation are considered as they have a high influence on the system performance and sizing process. Meteorological and load input data for the case studies analyzed is described. The implementation of the simulation model, multi-objective optimization, and sensitivity analysis is explained.

Figure 1 displays the considered direct current (DC) based SHS system with photovoltaic (PV) panel, charge controller, lead-acid battery, and DC loads.

Figure 1 Representation of considered SHS system configuration.

2.1. Mathematical model

This section describes the used mathematical models of all technical system components and the used simulation input data.

2.1.1. Photovoltaic model

The photovoltaic model consists of a power model, thermal model, and a simple degradation model. For its implementation, the pvlib library version 0.7.1 is used [22]. Utilized photovoltaic modules are the Pythagoras Solar Midi PVGU Window, Canadian Solar Inc. CS5C-80M, and Resonix EPML120W6Hall [23]–[25]. These modules show all a reasonable voltage level for the usage with a PWM charge controller and a nominal peak power in accordance with the considered system sizes (compare section 2.1.4). The meteorological input data with the considered photovoltaic inclination and orientation is described in section 2.1.5.

Power model

The photovoltaic power model computes the photovoltaic output power depending on the used charge controller technology. In the case of a PWM charge controller, the photovoltaic output power needs to be calculated at a specific voltage point. Therefore, the current-voltage relationship following the single-diode five parameter model by De Soto et al. is implemented [27]. The model is based on manufacturer datasheet information (compare Table 1), the absorbed solar irradiation, and the cell temperature together with semi-empirical equations. Datasheet information can be obtained from the CEC module database, which is available

on the National Renewable Energy Laboratory GitHub website [26]. The model is also used in the System Advisor Model software and described in detail in [28]. The following equations define the basic relationship of the single-diode model:

$$I = I_L - I_D - I_{sh} \quad (1)$$

$$I = I_L - I_0 \cdot \left(e^{\frac{V + I \cdot R_s}{a}} - 1 \right) - \frac{V + I \cdot R_s}{R_{sh}} \quad (2)$$

with I_L the light current in A, I_D the diode current in A, I_{sh} the shunt current in A, I_0 the diode reverse saturation current in A, V the photovoltaic voltage in V, R_s the series resistance in Ω , R_{sh} the shunt resistance in Ω and a the modified ideality factor. This factor is defined by the following equation:

$$a = \frac{N_s \cdot n_i \cdot k \cdot T_c}{q} \quad (3)$$

with N_s the number of cells in series, n_i the usual ideality factor, k the Boltzmann's constant ($1.38066 \cdot 10^{-23} \text{ J} \cdot \text{K}^{-1}$), q the electron charge and T_c the photovoltaic cell temperature in K.

The photovoltaic output power can then be calculated at a specific voltage point of the obtained current-voltage relationship with the product of voltage and current. It is assumed that the photovoltaic panel works at the battery voltage (compare section 2.1.3) and voltage losses due to cabling between battery and photovoltaic panel are neglected.

$$P_{PWM,PV} = I \cdot V_{battery} \quad (4)$$

In the case of a MPPT charge controller, it is assumed that the photovoltaic panel always works at its Maximum Power Point. Tracking losses are neglected. The model is based on the PVWatts Version 5 model (included in the used pvlib library version 0.7.1) and is defined by the following equation [29]:

$$P_{MPP,PV} = \frac{G_{poa}}{G_{STC}} \cdot (P_{dc0} \cdot (1 + \gamma_{pdco} \cdot (T_c - T_{STC}))) \quad (5)$$

with G_{poa} the total plane of array irradiance in $\text{W} \cdot \text{m}^{-2}$, G_{STC} the irradiance at Standard Test Conditions ($1000 \text{ W} \cdot \text{m}^{-2}$), P_{dc0} the photovoltaic peak output power at the Maximum Power Point and Standard Test Conditions in Wp, γ_{pdco} the temperature coefficient of the output power in $1 \cdot \text{K}^{-1}$, T_c the variable photovoltaic cell temperature in K and T_{STC} the temperature at Standard Test Conditions (298.15 K).

Relevant parameters and constants used for the photovoltaic model can be found in Table 1.

Table 1 Photovoltaic model parameter based on following modules [23]–[25] obtained from the CEC module list from [26].

Parameter	Unit	Pico System	Medium System	Large System
Photovoltaic panel type		Pythagoras Solar Midi PVGU Window	Canadian Solar Inc. CS5C-80M	Resonix EPML120W6H
P_{dc0}	Wp	20.3	80.2	121.5
V_{mp}	V	16.1	17.5	16.2
a		0.795311	0.976234	0.822578
I_L	A	1.351524	4.980938	8.117732
I_0	A	$3.37 \cdot 10^{-11}$	$6.69 \cdot 10^{-10}$	$2.17 \cdot 10^{-10}$
R_{sh}	Ω	633.18	148.16	82.86
R_s	Ω	0.714915	0.326085	0.181393
γ_{pdco}	$1 \cdot \text{K}^{-1}$	-0.005	-0.005	-0.005

Thermal model

The photovoltaic thermal model computes the cell temperature dependent on environmental conditions as solar irradiance, ambient temperature, and wind speed. The semi-empirical approach by King et al. is used [30]. The equation consists of two terms, from which the first describes the temperature of the photovoltaic module, while the second defines the temperature difference between the module and the cell itself. The following equation describes the thermal model:

$$T_c = (G_{poa} \cdot \exp^{a+b \cdot v_{wind}} + T_a) + \Delta T \cdot \frac{G_{poa}}{G_{STC}} \quad (6)$$

with G_{poa} the total plane of array irradiance in $\text{W} \cdot \text{m}^{-2}$, v_{wind} the wind speed in $\text{m} \cdot \text{s}^{-1}$, T_a the ambient temperature in K, and the empiric parameters for a glass/cell/polymer sheet module type with an open rack mounting, which are $a=-3.56$, $b=0.075$ and $\Delta T=3$ [30].

Degradation model

To include the proceeding degradation of a photovoltaic module and to determine the component state of destruction an annual degradation rate of the peak power of $0.5 \% \cdot \text{a}^{-1}$ is assumed in this study. This value corresponds to Linssen et al. [31].

2.1.2. Electronic model

The electronic model consists of a power model which defines the electronic component efficiency and a lifetime model.

Power model

The power model follows the approach by Sauer and Schmidt, which describes the power-dependent efficiency of photovoltaic inverters [32]. Its basic equation is:

$$\eta(P_{out}) = \frac{P_{out}}{P_{out} + (p_{self} + v_{loss} \cdot P_{out} + r_{loss} \cdot P_{out})} \quad (7)$$

with P_{out} the component output power in W and the model coefficients p_{self} , v_{loss} , and r_{loss} . The efficiency equation can also be defined depending on the component input power with the coefficients p_{self}^* , v_{loss}^* and r_{loss}^* :

$$\eta(P_{in}) = -\frac{1}{2 \cdot r_{loss}^* \cdot P_{in}} + \sqrt{\frac{(1 + v_{loss}^*)^2}{(2 \cdot r_{loss}^* \cdot P_{in})^2} + \frac{p_{in} + p_{self}^*}{r_{loss}^* \cdot P_{in}^2}} \quad (8)$$

The model coefficients p_{self} , v_{loss} , and r_{loss} are parametrized with power-dependent efficiency curves of the power component provided in most datasheets. Equations for the coefficient transformation are given in [32].

The MPPT charge controller is parametrized with the datasheet information of the HQST MPPT Solar Charge Controller [33]. Power-dependent efficiency curves of PWM charge controllers could not be identified. It is further dependent on the switching frequency, which correlates with the battery charge level. Therefore, the power-dependent efficiency curve is estimated with the assumption of a mean switching cycle. The obtained efficiency curves of the PWM and MPPT charge controller lie slightly above the mean values of the study by Laguado et al., which compares the performance of these two types of charge controller [13]. Figure 2 presents the used power-dependent efficiency curves of both charge controller technologies, Table 2 shows the identified model parameters.

Figure 2: Power-dependent efficiency curves of considered charge controller technologies.

Table 2 Model parameter of considered charge controller technologies [34].

Component	p_{self}	v_{loss}	r_{loss}	$\eta_{nominal}$
MPPT	0.002671	0.009737	0.031432	0.951
PWM	0.002212	0.134184	0.055497	0.839

Lifetime model

For the charge controller, a lifetime of 10 years without dynamic power degradation is assumed, from which the component state of destruction can be calculated.

2.1.3. Battery model

The battery model consists of a state model, which defines charge and discharge efficiencies, cut-off boundaries, state of charge and voltage, a thermal model, and a degradation model, which computes the capacity loss due to calendric and cycle aging. A lead-acid battery is considered as it is a low-cost and readily available storage technology [8]. The model is parametrized with the battery Ritar OPzV 100, which is a 12 V battery with a 100 Ah capacity [35].

State model

The power-dependent charge and discharge efficiencies and cut-off boundaries are based on the method presented by Schmid et al. [36]. The model assumes a simple equivalent circuit with a power-dependent resistance for the charge and discharge process. The model is parametrized with the fitted battery charge and discharge curves (voltage–state of charge (SoC) correlation) at different C-rates, using the mathematical formulation by Tremblay et al. [37]. Applying the ohmic law the internal resistance of the cell can be determined with curves at different C-rates and therewith the efficiency of the battery cell. Following linear equations describe the charge and discharge efficiencies:

$$\eta_{CH}(C\text{-rate}) = 1 - 0.2282 \cdot C\text{-rate} \quad (9)$$

$$\eta_{DCH}(C\text{-rate}) = 1 - 0.6327 \cdot C\text{-rate} \quad (10)$$

Cut-off boundaries can be extracted from the power-dependent charge and discharge curves on given C-rates. An additional safety margin (cut-off voltage at 11.9 V) to hinder the deep discharge of the lead-acid battery is included. Boundaries are defined by the following linear equations:

$$SoC_{cut\ off,CH}(C\text{-rate}) = 1.1240 - 1.2757 \cdot C\text{-rate} \quad (11)$$

$$SoC_{cut\ off,DCH}(C\text{-rate}) = 0.3070 + 0.4870 \cdot C\text{-rate} \quad (12)$$

The battery charge and discharge voltages are described by polynomial functions taking the battery power and state of charge into account. The curve fitting with the charge and discharge curves describing the battery voltage for different power and state of charge levels is done using the method of least squares. Battery discharge curves show a linear behavior (in contradiction to charge curves), which makes the quadratic terms dispensable. The voltage is described by the following equations:

$$V_{CH}(P_T, SoC) = 2.5109 \cdot SoC^2 - 8.7 \cdot 10^{-5} \cdot P_T^2 + 0.0093 \cdot SoC \cdot P_T - 0.9976 \cdot SoC + 0.0185 \cdot P_T + 11.9241 \quad (13)$$

$$V_{DCH}(P_T, SoC) = 1.2981 \cdot SoC - 0.0017 \cdot P_T + 11.5240 \quad (14)$$

with SoC the battery state of charge and P_T the battery terminal power in W.

The battery state of charge is defined by a simple energy balance for every simulation step using an off-line book-keeping method, which is also used by Schmid et al. [36]. It is defined by the following equation:

$$SoC(t) = SoC(t-1) + \frac{(P_T - P_{loss,total} - P_{self-discharge}) \cdot dt}{E_{actual}} \quad (15)$$

with $P_{loss, total}$ the charge and discharge losses in W, $P_{self-discharge}$ the battery self-discharge power in W (calculated with the relative capacity loss of $1.1421 \cdot 10^{-8} \text{ s}^{-1}$ from the datasheet and the current battery capacity), dt the timestep in hours, and E_{actual} the current battery capacity in Wh.

Thermal model

The thermal model follows a simple heat balance integrating the ohmic losses and the convective heat exchange to the environment. The following equation defines the battery temperature in every timestep:

$$T_b(t+1) = \frac{P_{loss,total} - h \cdot (A \cdot E_{actual}) \cdot (T(t) - T_a(t)) \cdot dt}{(m \cdot E_{actual}) \cdot c_p} + T(t) \quad (16)$$

with h the heat transfer coefficient in $\text{W}\cdot\text{m}^{-2}\cdot\text{K}^{-1}$, A the surface-specific energy $\text{Wh}\cdot\text{m}^{-2}$, m the mass-specific energy in $\text{Wh}\cdot\text{kg}^{-1}$ and c_p the average battery heat capacity in $\text{J}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$. Table 3 gives an overview of used battery parameters.

Table 3 Battery thermal model parameter [35].

Parameter	Unit	Value
h	$\text{W}\cdot\text{m}^{-2}\cdot\text{K}^{-1}$	2.0
A	$\text{Wh}\cdot\text{m}^{-2}$	5843.0
m	$\text{Wh}\cdot\text{kg}^{-1}$	256.0
c_p	$\text{J}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$	850.0

Degradation model

The battery degradation model considers cycle and calendric capacity loss. In case of a power flow, the battery degradation follows the cycle aging model and in case of no power flow, the calendric degradation model is applied.

The cycle aging is based on the lifetime model proposed by Narayan et al. [12] and considers the depth of discharge dependency of the lifetime given in the battery datasheet. The following polynomial approximation function defines the lifetime-depth of discharge correlation and calculates the number of cycles until the end of life:

$$\text{cycle life}(DoD) = -5168.16 \cdot DoD^3 + 14868.72 \cdot DoD^2 - 15792.13 \cdot DoD + 7008.82 \quad (17)$$

To dynamically integrate the capacity degradation Narayan et al. propose the zero-crossing micro-cycle approach. A zero-crossing micro-cycle is defined as the time between two subsequent states where the battery power is zero. After every micro-cycle, its mean depth of discharge is determined and the capacity degradation of this micro-cycle with the given polynomial equations is calculated:

$$\overline{DoD} = \frac{\sum_{n=0}^N DoD_i}{N} \quad (18)$$

$$\text{cycle life}_{\text{micro-cycle}} = \text{cycle life}(\overline{DoD}) \quad (19)$$

with the timestep n to N and the polynomial function defined in equation (17). The relative and absolute capacity degradation of each micro-cycle are then calculated with the following equations:

$$C_{\text{relative loss, micro-cycle}} = \frac{E_{\text{micro-cycle}} / (2 \cdot C_{\text{nominal}} \cdot \overline{DoD})}{\text{cycle life}_{\text{micro-cycle}}} \quad (20)$$

$$C_{\text{loss, micro-cycle}} = C_{\text{relative loss, micro-cycle}} \cdot (C_{\text{nominal}} - C_{\text{end of life}}) \quad (21)$$

with $E_{\text{micro-cycle}}$ the energy cycled during the micro-cycle in Wh, C_{nominal} the nominal battery capacity in Wh, and $C_{\text{end of life}}$ the battery end of life capacity in Wh.

The calendric loss is based on the temperature dependency of the float lifetime given in the battery datasheet. The following equations define the polynomial approximation function for the lifetime in years and the absolute capacity loss per timestep:

$$\text{calendric life}(T_b) = 7.70e^{-10} \cdot T_b^{-5} + 0.0002 \cdot T_b^{-5} + 33.30 \cdot T_b^{-5} - 5352.17 \quad (22)$$

$$C_{\text{loss, calendric}} = \frac{(C_{\text{nominal}} - C_{\text{end of life}})}{\text{calendric life}(T_b) \cdot 8760} \quad (23)$$

2.1.4. Load profile

The definition of the load profile is a crucial part of the SHS sizing process [38]. Creating representative load patterns is a complex task due to little knowledge of user behavior and the lack of standard load profiles. Mandelli et al. propose a bottom-up methodology to generate load profiles based on microscopic usage data [39]. Almeida et al. provide average appliance energy consumption for a generic african household with the underlying appliances used [40]. Nevertheless, the load profile is highly dependent on the available appliances and therefore

from the SHS size category bought. For the current study, three different SHS size categories are considered, according to [5]. These are:

1. **Pico System:** SHS entry level with typical installed photovoltaic power in the range of 11 to 20.99 Wp. Appliances involve lights, radio, and phone chargers. The system enables partial Multi-Tier Framework Tier 1 electricity access.
2. **Medium System:** SHS with medium capacity with typical installed photovoltaic power in the range of 50-99.99 Wp. Appliances involve Pico System appliances with extended runtime and television. The system enables full Multi-Tier Framework Tier 2 Electricity Access.
3. **Large System:** SHS with higher capacity with typical installed photovoltaic power higher than 100 Wp. Appliances are comparable to Medium system appliances with increased runtime. The system enables full Multi-Tier Framework Tier 2 Electricity Access.

Daily load profiles with an hourly resolution based on typical appliance runtimes given in specification sheets by Lighting Global certified products are generated [7]. Considered appliances (Lights, Radio, Phone charger, TV) show no variable power consumption in a resolution of minutes, as it is the case for fridges or washing machines. Therefore, the used hourly resolution of the simulation can be seen as sufficient.

Table 4 gives an overview of the assumptions made for the profile synthesization, as the number and nominal power of appliances and their usage duration.

Table 4 Load profile synthesization parameter.

Appliance	Number	Usage duration [h]	Power [W]
Lights	2 / 8 / 8	13 / 13 / 13	2 / 2 / 2
Radio	1 / 1 / 1	3 / 4 / 6	3.5 / 3.5 / 3.5
Phone charger	1 / 1 / 1	2 / 3 / 5	5 / 5 / 5
TV	0 / 1 / 1	0 / 4 / 6	0 / 15 / 24

Figure 3 presents the three load profiles generated for the Pico, Medium, and Large System.

Figure 3 Generated load profiles for all three SHS categories.

The generated load profiles follow the general shape of the load profiles provided by Almeida et al. with the characteristic morning and evening peak [40]. Detailed analysis of the definition of load profiles for SHS is not the subject of this study.

2.1.5. Meteorological data

For the consideration of different climatic and irradiance conditions in sub-saharan africa, three case study locations were selected. Case studies are situated in east, west, and central/south africa, which are the main SHS markets in sub-saharan africa [5]. As case studies differ in their geographical location, optimal photovoltaic orientation and tilt angle change as well. Optimal tilt angles according to Jacobson et al. with south orientation for systems situated in the northern hemisphere and north orientation for systems in the southern hemisphere are used [41]. A possible double-sided photovoltaic orientation with south-east and south-west (and north accordingly) orientation, which could improve the share of direct used photovoltaic energy, is neglected. Due to

the necessary small installed photovoltaic peak power, usually, only one photovoltaic panel is installed, which makes double-sided orientation impossible. The three case studies with its photovoltaic orientation are:

- Porto Novo, Benin (2.6253, 6.4991), photovoltaic orientation (south and 10° inclination)
- Arusha, Tanzania (36.6830, -3.3869), photovoltaic orientation (north and 10° inclination)
- Uppington, South Africa, (21.2483, -28.4523), photovoltaic orientation (north and 26° inclination)

The irradiance data from the Copernicus Programme Atmosphere Monitoring Service is used. Global, beam, and diffuse irradiance on the horizontal plane is provided in an hourly resolution since 2004. It is based on the data from geostationary orbit satellites and can be downloaded free of charge [42]. Data on ambient air temperature, humidity, and wind speed is based on the MERRA database provided by the NASA Godard Space Flight Center [43]. For the current study, the timeframe from 01.01.2010 till 01.01.2020 with an hourly resolution is used. A brief overview of the main environmental parameters is presented in Table 5.

Table 5 Main environmental parameters of considered SHS locations for the three case studies.

Parameter	Unit	Porto Novo	Arusha	Uppington
Mean irradiation	$\text{kWh}\cdot\text{m}^{-2}\cdot\text{a}^{-1}$	1709.13	2049.25	2214.77
Max irradiance	$\text{W}\cdot\text{m}^{-2}$	956	1141	1208
Mean temperature	K	299.6	294.8	294.0

2.2. Economic model

The costs of SHS components in sub-saharan africa vary greatly between different products [3]. Therefore, cost assumptions involve a high degree of uncertainty. In respect to the generic approach of this study, general economic assumptions for the component investment costs (CC), operation and maintenance costs (OMC), and balance of system costs (BOS) are assumed. A correlation between increasing system sizes and lower specific costs per Wp is neglected because a clear relation is difficult to estimate [3] and only a small photovoltaic panel power range is considered (compare Table 8). PWM investment costs are specified to be 25 % of MPPT investment costs. This is according to the cost relationship of the Victron BlueSolar PWM-Light 10A and the Victron Smartsolar MPPT 75/10 10A charge controller [44], [45]. Further, it is based on personal communication with a SHS manufacturer. Table 6 gives an overview of the economic assumptions made.

Table 6 Cost parameters for the economic model.

Cost component	Unit	Value	Reference
CC Photovoltaic	$\text{\$}\cdot\text{Wp}^{-1}$	1.500	[3]
CC Battery	$\text{\$}\cdot\text{Wh}^{-1}$	0.208	[3]
CC MPPT	$\text{\$}\cdot\text{Wp}^{-1}$	0.525	[3], [40]
CC PWM	$\text{\$}\cdot\text{Wp}^{-1}$	0.131	[44], [45]
BOS	$\text{\$}\cdot\text{Wp}^{-1}$	1.000	[3]
OMC	$\%\cdot\text{CC}_i$	3.0	-
Annual percentage rate	%	5.0	-

As we analyze stand-alone systems for un-productive use in remote areas and no grid-connected SHS, which are more common in areas with unreliable grid connection, we do not consider any backup power source costs (like grid costs or diesel generator costs). Further generators are rare in the analyzed customer segment of SHS but more common in mini-grid applications with an installed power capacity of multiple kilowatts [5].

2.3. Simulation model

The numeric power flow simulation follows an object-oriented programming approach and is written in the high-level language Python™ 3.7. It is published on GitHub¹ under the Creative Commons Attribution-ShareAlike 4.0 International License and is developed based on the continuous work on the simulation tool by Schmid et al. [36]. For the current study, the simulation considers a 10-year timeframe with an hourly resolution.

The SHS sizing process aims to find the optimal size of system components under the consideration of environmental and user behavior boundary conditions. For the assessment of system alternatives, different

¹ <https://github.com/fabmid/Open-Energy-Cell-Simulation>

objective functions are used. Objective functions can involve technical, ecological, or economic performance indicators. Khatib et al. provide a detailed overview of objective functions for the sizing of photovoltaic battery standalone systems [46]. In this study, the common key figure LCoE is used for economic quantification. For the determination of energy security, the number of days with PCO is used as a technical indicator.

The LCoE is calculated according to the following equation:

$$LCoE = \frac{ATLCC}{E_{load\ supplied}} = \frac{\sum_k A_{cc,k} + A_{omc,k} + A_{rc,k} + A_{rv,k}}{E_{load\ supplied}} \quad (24)$$

with ATLCC the annual levelized cost flow in $\$/a^{-1}$, $E_{load\ supplied}$ the supplied load energy in Wh, $A_{cc,k}$ the annuity of investment costs of all components k in $\$/a^{-1}$, $A_{omc,k}$ the annuity of the operation and maintenance costs of all components k in $\$/a^{-1}$, $A_{rc,k}$ the annuity of replacement costs of all components k, in case it reaches its end of life in $\$/a^{-1}$ and $A_{rv,k}$ the residual value of all components k. The residual costs of the component k are calculated according to the following equation:

$$A_{rv,k} = CRF \cdot \frac{SoD_{k,t} \cdot CC_{k,t}}{(1 + i_{eff})^t} \quad (25)$$

with CRF the capital recovery factor, $SoD_{k,t}$ the state of destruction of the component k at the time t (is zero for a new component and one for an end-of-life component), $CC_{k,t}$ the investment costs of component k at the time t and i_{eff} the annual percentage rate. We do not consider any disposal costs for components at their end-of-life as this can not be estimated comprehensibly. It is further questionable if disposal costs occur in cultures and economies of repair, which are in place in sub-saharan africa and have a potential for an alternative approach of solar waste handling [47].

For the technical objective the new figure, the number of days with PCO is considered, which is the mean value of days per year with any power cut-off during the simulation timeframe. This shall reflect the user's perspective in a better way, which sees dominantly the power cut-off and not the amount of energy that is lost.

2.4. Multi-objective optimization

In general, a multi-objective optimization seeks the solution of a problem with conflicting objectives. An optimization solution x_1 is said to (Pareto)-dominate another solution x_2 if it is at least as good as x_2 for all the objectives, and strictly better at least for one objective. The set of Pareto optimal solutions is called the Pareto set, while the image of this set is called the Pareto front. The multi-objective optimization procedure aims to approximate the Pareto set by minimizing the distance between the approximation and the Pareto front while presenting a good distribution and wide extent of the Pareto front approximation [48].

The optimization procedure in this study is based on the developed simulation model and the defined objective functions, which shall be minimized. The multi-objective genetic algorithm NSGA II (Non-Sorting Genetic Algorithm) with a posteriori method is implemented according to Deb et al. [49]. The NSGA II seeks for the best approximation of the Pareto set and shows compared to other multiobjective optimization algorithms a good solution distribution and Pareto set approximation [49]. Nevertheless, due to its meta-heuristic characteristic, we refer in the following to the Pareto set/front approximation. Audet et al. review state-of-the-art performance indicators for the Pareto front quality measurement [48]. Authors state that up to date the hypervolume/hyperarea (HV) metrics can be considered as the most relevant one and indicates performance regarding convergence and distribution. To justify the algorithm selection, the NSGA II algorithm is compared with some state-of-the-art genetic algorithms (NSGA III, CMAES, MOEAD, OMOPSO, SPEA2) on the DTLZ2 test problem from Deb et al. [50] with two objectives using the hypervolume/hyperarea as the main performance indicator. Further, the Generational Distance (GD) and Inverted Generational Distance (IGD) are presented, although their significance is limited due to their inability to capture dominance relation [48].

Table 7 Performance indicators of state-of-the-art genetic algorithms [51].

Algorithm/Indicator	HV	GD	IGD
NSGAI	0.2352	0.0026	0.0048
NSGAIII	0.2040	0.0118	0.0353
CMAES	0.2073	0.0127	0.0399
MOEAD	0.2016	0.0135	0.0370
OMOPSO	0.2074	0.0139	0.0405

SPEA2	0.2360	0.0115	0.0043
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Table 7 presents the results of analyzed performance indicators. The choice of NSGA II is justified by superior values over the compared algorithms for the hyperarea indicator as well as for the Generational Distance and Inverted Generational Distance, which proofs a good Pareto set approximation of NSGA II.

To solve the present multi-objective optimization problem of SHS sizing, Table 8 provides all input and output parameters and data applied. It presents the simulation model inputs, NSGA II algorithm parameter set up, which is defined according to standard values by [49], as well as the decision variables and objective functions with their constraints.

Table 8 Overview of input and output parameters and data of the optimization problem.

Simulation	Load profile of three considered categories Pico, Medium, Large SHS (compare section 2.1.4) Meteorological data for three considered locations 01.01.2010 - 01.01.2020 (compare section 2.1.5) Economic parameters (compare table 6 in section 2.2 and section 2.3)	
Algorithm parameter	Population size	100
	Generations	1100
	Mutation	1.0
	Crossover probability	1.0
	Mutation distribution	20.0
	Crossover distribution	15.0
Decision variables	Photovoltaik peak power	Pico Systems: $5 \leq P_{dc0} \leq 120 \text{ Wp}$ Medium Systems: $20 \leq P_{dc0} \leq 200 \text{ Wp}$ Large Systems: $20 \leq P_{dc0} \leq 400 \text{ Wp}$
	Battery capacity	Pico Systems: $5 \leq C_{nominal} \leq 600 \text{ Wh}$ Medium Systems: $200 \leq C_{nominal} \leq 1200 \text{ Wh}$ Large Systems: $200 \leq C_{nominal} \leq 2400 \text{ Wh}$
Objective functions	Levelized Cost of Electricity	$0 \leq LCoE \leq 2 \text{ \$} \cdot \text{kWh}^{-1}$
	Power Cut Offs	$0 \leq PCO \leq 100 \text{ d} \cdot \text{a}^{-1}$

The decision variables cover the photovoltaic peak power and battery capacity, while the charge controller power is sized according to the obtained optimal photovoltaic peak power. Cost savings through an undersizing of the charge controller are neglected and the nominal controller power is fixed to the optimal photovoltaic peak power.

For comparison of different obtained Pareto front approximations, a simple exponential curve fitting ($f(x) = a \cdot e^{b \cdot x}$) is applied. As front approximations show a uniform distribution over the objective space, it is assumed that more elaborated methods as curve estimation proposed by Binois et al. are not necessary for this purpose [52], [53].

2.5. Sensitivity analysis

In order to analyze the robustness of results of the approximate set of Pareto-optimal solutions, an a-posteriori sensitivity analysis is conducted. The sensitivity of the two objective functions regarding changes of input data is examined. Therefore, the stochastic concept of a Monte Carlo simulation for the evaluation of processor-intensive models and their results is applied [54].

Three sensitivity cases, namely irradiance, load, and economic are considered. Therefore, normally distributed random factors with an individual relative standard deviation for the solar irradiance, load profile, PWM, and MPPT investment costs are generated. The solar irradiance is varied for each timestep with a relative standard deviation of 12 % [55]. Annual irradiation level is kept constant at this randomization step and varied in the next step by a relative standard deviation of 1.72 %, which is determined by the analysis of the last 10-year annual irradiance data. Each load profile timestep and the PWM and MPPT charge controller investment costs are randomized with an assumed relative standard deviation of 15 %. Charge controller investment costs are varied with individual random factors for MPPT and PWM controller which changes not only the absolute value but also

the cost ratio of the two technologies. Therefore, irradiance and load are randomized for every timestep, while PWM and MPPT charge controller investment costs for each simulation run, which is repeated for 100 Monte Carlo simulation runs.

3. RESULTS

This section presents the main results and discussion of the influence of charge controller technology on optimal SHS sizing. First Pareto front approximations for all considered case studies are examined. Second, a detailed look at Pareto-optimal system configurations with installed photovoltaic peak power and battery capacity is analysed in the same context. Third, the influence of charge controller technology on Peak Sun Hours (PSH) and battery SoC is presented. Finally, a sensitivity analysis shows the influence of different input parameters on system performance metrics.

3.1. Multi-objective optimization

Figure 4 shows the obtained Pareto front approximations from the multi-objective optimization for all system sizes with PWM and MPPT charge controller at all considered locations. Pareto front approximations of non-dominated solutions are fitted with an exponential function and cost differences between the two fitted fronts are displayed as horizontal bar plots with its mean value as a dashed line. In all cases, a lower LCoE for the same number of PCO is achieved by the implementation of a MPPT charge controller. The difference in cost savings is dependent on the number of PCO, system size, and location. There is no consistent correlation between higher cost savings with decreased or increased number of PCO and with the location and thereby with the irradiance level apparent. But cost savings increase for all locations between the Pico and Medium System for the same number of PCO. Mean cost savings between fitted Pareto front approximations are in the range of 4.2 % to 5.6 % for the Pico System and 8.0 % to 8.6 % for the Medium System. The Large System deviates from this trend with mean cost savings between 4.0 % and 6.5 %.

Figure 4 Pareto front approximations for all system sizes and locations, exponential fitting functions are displayed as dotted black line, cost differences between fitting function of MPPT and PWM fronts are displayed as bar-plot in percentage of LCoE cost savings and its mean value (dashed line).

Figure 5 shows system configurations of the Pareto front approximation for all system sizes at the location Porto Novo. In general, the installed photovoltaic peak power and battery capacity increase towards a smaller number of PCO for all system sizes and independent from the charge controller technology. Systems with a MPPT charge controller show lower installed photovoltaic peak power compared to systems with PWM technology. The mean

values of the approximate Pareto-optimal solutions with the same number of PCO show a decrease of 34.7 % (Pico System), 38.6 % (Medium System), and 31.2 % (Large System). Furthermore, charge controller technology shows an influence on the optimal installed battery capacity with slightly lower installed capacities for systems with MPPT compared to PWM. The mean values show a decrease of 8.8 % (Pico System), 5.4 % (Medium System), and 2.8 % (Large System).

As expected, the charge controller technology has a major influence on the approximate Pareto-optimal photovoltaic power installed and main cost savings can be reached through reduced panel sizes. Therefore, higher costs for the MPPT charge controller are mainly balanced by a smaller installed photovoltaic peak power, and even cost savings can be reached. Further, a reduced battery capacity influences the economics of the systems, especially as the battery component is the main cost driver for SHS. In general, the result that relevant cost savings through a MPPT implementation can be reached even for Pico SHS is in contradiction to the assumption in the literature [14].

Figure 5 Pareto front approximations with optimal installed photovoltaic peak power and battery capacity for the charge controller technologies PWM and MPPT for all system sizes at the location Porto Novo.

The obtained approximate Pareto-optimal installed photovoltaic peak power for systems with a MPPT charge controller are in good correlation with typical panel sizes of this product category [5]. But it becomes obvious that the information of the implemented charge controller, which is normally not indicated in product brochures (e.g.[7]), is of particular importance to evaluate system capability and sizing.

For the analysis of system capability dependent on the implemented charge controller technology, a Medium Reference System at Porto Novo with 70 Wp installed photovoltaic peak power and 800 Wh battery capacity is analyzed in detail. In the case of an implemented MPPT charge controller, the system shows a PCO of 3 d·a⁻¹ and lies at the Pareto front approximation. While the same system with PWM shows a PCO of 169 d·a⁻¹ and is located in the dominated solution space. Figure 6 shows the daily battery state of charge evolution for the 10-year simulation timeframe. The mean state of charge lies with implemented MPPT at a SoC of 0.91, while it is considerably lower at a SoC of 0.56 for an implemented PWM charge controller. To properly assess these results, it should be noted that under no-load operation the minimum SoC lies at 0.3070 (compare equation (11)) and the maximum SoC at 1.1240 (compare equation (12)). The state of charge of the system with an installed PWM charge controller remains low and is often at its discharge cut-off boundary for multiple months (a seasonal effect is apparent). This influences the battery lifetime as a regular full battery charge is necessary to guarantee

long battery performance and hinder capacity degradation via sulfation and active material softening [10]. The sizing of the battery bank is in strong correlation with the installed photovoltaic peak power. An oversized battery capacity with an undersized photovoltaic power most probably results in faster battery degradation and shorter system lifetimes. On the other side, an undersized battery bank results in regular power cut-offs during night load. Therefore, not only installed photovoltaic peak power and battery capacity is necessary system information but also charge controller technology.

Figure 6 Battery state of charge for a 70 Wp / 800 Wh system with MPPT and PWM at Porto Novo.

The PSH describe the amount of daily energy yield by the photovoltaic module per installed Wp. The photovoltaic output power (including losses due to inclination and azimuth angle, excluding charge controller losses) is used for the energy yield determination. Figure 7 presents the achieved PSH by using a MPPT and PWM charge controller for the 70 Wp photovoltaic panel at Porto Novo. The MPPT system achieves a mean value of $4.13 \text{ Wh} \cdot \text{Wp}^{-1}$, while the PWM system lies at $3.52 \text{ Wh} \cdot \text{Wp}^{-1}$ (decrease of 14.8 %). Especially during morning and evening hours the MPPT system can harvest a substantially higher percentage of energy and can generate a photovoltaic current at ambient conditions where the PWM charge controller is unable to do so. This expands the timeframe of direct photovoltaic usage and therefore relieves battery load.

Figure 7 Boxplots of daily PSH of a 70 Wp photovoltaic panel with MPPT and PWM controller at Porto Novo, blue square is indicating the arithmetic mean (left) and hourly PSH difference expressed as percentage over the daytime (right).

In general, it can be stated, that the implementation of a MPPT charge controller increases the system energy efficiency and reduces the resource consumption through smaller system components for all considered SHS size categories.

3.2. Sensitivity analysis

A sensitivity analysis is conducted for approximate Pareto-optimal MPPT and PWM Medium Systems at the location Porto Novo. System sizing is done according to the obtained Pareto-optimal approximate solutions with a PCO of $3 \text{ d} \cdot \text{a}^{-1}$. The MPPT system shows 70 Wp and 800 Wh with a LCoE of $0.535 \text{ \$} \cdot \text{kWh}^{-1}$, while the PWM system shows 97 Wp and 840 Wh with a LCoE of $0.588 \text{ \$} \cdot \text{kWh}^{-1}$ (compare Figure 5).

Figure 8 shows all Monte Carlo simulation runs for the variation of solar irradiance, load profile, and economic investment costs of PWM and MPPT charge controller. The variation of the solar irradiance level shows mainly influence on the PCO, while the LCoE for systems with MPPT and PWM and the identified cost savings remain

constant. LCoE and PCO show high sensitivity regarding the load profile, with a brought variation on both parameters. But cost savings remain quite constant for all simulation runs with the same number of PCO. As expected, a variation of the economic parameter PWM and MPPT investment costs show no influence on PCO but LCoE. The mean cost savings of all simulation runs remain constant, while the LCoE differs for individual runs.

Figure 8 Monte Carlo simulation results for the sensitivity cases irradiance, load and economic. Scatter plots present obtained values of LCoE and PCO, while histograms present their distribution with the frequency as number of cases. Dashed line is representing LCoE arithmetic mean off all Monte Carlo simulation runs.

Figure 9 represents the LCoE cost savings dependent on generated random factors for the variation of PWM and MPPT investment costs. Mean cost savings are at 10.1 %, which is in the range of the obtained cost savings identified by the difference in Pareto front approximations (compare Figure 4). Cost savings are more dependent on the variation of MPPT costs than PWM costs and decrease with an increase in the random factor for MPPT investment costs. This can be explained through the fact, that investment costs for a MPPT charge controller are higher than for a PWM charge controller, but both are assumed to have the same relative standard deviation. Therefore, MPPT costs increase stronger than PWM costs. In this context, it needs to be mentioned that photovoltaic investment costs are likely to be lower for panels with higher maximum power voltage than considered in this study, which were specifically identified for the usage with PWM charge controllers. This is supported by Müller et al., who state that a wider choice of photovoltaic panels can be used in combination with an MPPT [15]. These potential cost savings are therefore untracked in this methodology and could further reduce the overall cost difference of these two systems.

Figure 9 Monte Carlo simulation results for the economic sensitivity case with random factor generation for PWM and MPPT charge controller costs and its influence on LCoE cost savings between systems with MPPT and PWM.

In general, it can be stated that LCoE cost savings are robust regarding the variation of solar irradiance and load profile and investment costs of charge controller technologies.

4. CONCLUSION

In this study, the influence of MPPT and PWM charge controller technologies on Pareto-optimal SHS sizing was examined using a numerical power flow simulation and multi-objective optimization with the objective functions PCO and LCoE. Three different SHS sizes at three case studies in sub-saharan africa were analyzed using a 10-year simulation timeframe with an hourly resolution. Through the implementation of a MPPT charge controller mean LCoE savings in the range of 4.0 % to 8.6 % could be identified dependent on system size and location. Higher charge controller costs can be saved by reduced necessary photovoltaic peak power (by 31.2 % to 38.6 %) and battery capacity (by 2.8 % to 8.8 %). It is shown that the use of MPPT charge controllers increases energy efficiency, reduces resource consumption through reduced system component sizes, and shows a promising solution to reduce system costs, even for the smallest SHS sizes.

These results have a high significance for optimal SHS design, as they are contrary to the often-applied practical statement, that PWM charge controllers are advantageous for smaller system sizes. The Monte Carlo simulation shows the robustness of obtained LCoE cost savings regarding the variation of solar irradiance, load profile, and charge controller investment costs. The highest influence on cost savings reveals the investment cost assumptions with savings between 6 % and 16 % at a mean value of 10.1 %. Further, the presented influence of charge controller technology on the expectable PSH and battery state of charge highlights the lack of controller technology specification on most system datasheets. SHS manufacturers withhold customers valuable information to assess the full system capability.

Even significantly higher MPPT investment costs than PWM costs cannot balance out the identified cost savings. But it needs to be stated, that the general economic assumption made in this study, may not represent universal real-life component costs and should be adapted to specific cases. Therefore, this study gives SHS manufacturers the basis for a case-specific analysis of whether the use of MPPT controllers can be not only technical but also economically advantageous.

Future research should focus on the influence of different cost assumptions on the system economics and involve site-specific economic values to reduce the uncertainty of these parameters. The authors strive for cooperation with a SHS manufacturer to apply developed methods to real-life cases. The developed numeric simulation tool can be used for such future research as it is open-source and models can be easily parameterized with datasheet data. In general, this can help to improve SHS sizing in the practical field, guarantee optimal system performance and lifetime, as well as provide technology decision support.

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