Master's Thesis – Master Energy Science
Planning electricity access solutions for refugee settlements

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Abstract

Electricity access in refugee settlements is limited and mostly provided by diesel generators. A solution for improving this is to use sustainable mini-grids running on solar energy and batteries. This research aimed to build a pre-feasibility planning model that can compute the mini-grid's size for displacement settlements in Sub-Saharan Africa. In addition, the model must compute relevant techno-economic indicators to evaluate alternative configurations, based on scarce input data. To achieve this, the KALO Excel model built by Baldi (2021) was reproduced in Python, with a betters structure, a shorter running time and a lower sensitivity to human errors. Subsequently, three larger model improvements were implemented based on a literature review.

The result of this research is a Python model that can compute the daily load profile, the mini-gird's size and techno-economic indicators for the 288 camps in Sub-Saharan Africa. It uses simple camp-specific input data such as the population hosted in the camp, the average family size and the average daily peak sun hours. The only input required for the user is defining the scenario and whether to run the model for one or all camps. The computational time to run for all camps is reduced to only a few minutes. One output CSV file is created for each run.

In addition, the model allows comparing technological alternatives for electricity access in refugee settlements. These include a fully sustainable mini-grid, a hybrid mini-grid with diesel and grid extension. It was found that the Levelized Costs of Electricity are lower for fully renewable mini-grids than for hybrid ones. It was also found that grid extension is more attractive than a mini-grid for large camps and for camps close to the grid. However, an important limitation is that the latter comparison is only made based on costs, and that grid availability and sustainability are not considered. Lastly, load profiles for water pumping and purification were included in the demand. This reduced the LCOE of a mini-gird.

The model outcomes give a macro perspective of the requirement to provide electricity access in refugee settlements for different locations. The output is relevant for UNHCR, as they can create pipeline projects and implementation plans per region, based on this data.

Acknowledgements

This thesis was written to complete the Master's Program of Energy Science at Utrecht University. Another student of Utrecht University built the KALO-model, which was able to find sustainable mini-grid sizes for all refugee camps in Sub-Saharan Africa. This research builds further upon this work. Personal affection for the refugee and modelling context were motivations for the author to take on this topic.

First, I would like to express my sincere gratitude to my supervisor Elena Fumagalli for her support. Her feedback, ideas, understanding of the research topic and experience in the field helped me do this research, despite my little experience with this research topic. In addition, I would like to thank Duccio Baldi, on whose work this thesis is based. He was always open to questions and clearly explained the KALO-model he produced. This helped me build the model in Python and improve it where necessary. I also wish to thank Matteo Gazzani, the second reader of this thesis, for his time and feedback on this research. Lastly, I want to thank family and friends for their support during the final months of my Master's program.

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Abbreviations and Acronyms

CLOVER	Continuous Lifetime Optimization of Variable Electricity Resources
CF	Corrective Factor
COE	Cost Of Electricity
CSV	Comma-separated values
ECR	Electrification Coverage Rate
EMG	Existing Mini-Grid
GE	Grid Extension
GPA	Global Plan of Action
HOMER	Hybrid Optimization of Multiple Electrical Renewables
HRES	Hybrid Renewable Energy Systems
IDE	Integrated Development Environment
IDP	Internally Displaced People
LCUE	Levelized Cost of Used Electricity
LCOE	Levelized Cost Of Electricity
LP	Load Profile
MG	Mini-Grid
NPC	Net Present Cost
O&M	Operation and Maintenance
PV	Photo Voltaic
SDG	Sustainable Development Goal
Spyder	Scientific Python Development Environment
SSA	Sub-Saharan Africa
UNHCR	United Nations High Commissioner for Refugees
USD	US Dollar
VAT	Value Added Tax
WACC	Weighted Average Cost of Capital

1. Introduction

1.1. Societal background

The United Nations High Commission of Refugees (UNHCR) estimated that 82.4 million people were forcibly displaced in 2020. Of this number, 26.4 million were refugees, 48 million were internally displaced people (IDP), 4.1 million were asylum seekers and 2.9 million were Venezuelans displaced abroad. In addition, 86% of the refugees and Venezuelans were hosted in developing countries. Forcibly displaced people are forced to leave their homes, which can be caused by persecution, conflict, violence, human rights violations or events that seriously disturb public order. A person is considered a refugee when they cross a border to find safety. IDP have not crossed a border and are still under the protection of their government. The UNHCR is legally bounded to protect and assist refugees. While this is not the case for IDP, humanitarian organizations like UNHCR make little to no distinction and attempt to help all displaced people (Ryan & Childs, 2002). The continent of Africa hosted almost 6.6 million refugees by the end of 2020, which equals almost 27% of the global number of refugees (UNHCR, 2021). These refugees are divided over about 300 camps (Baldi, 2021).

Sustainable development goal (SDG) 7, which is called "Affordable and Clean Energy", is about ensuring access to affordable, reliable, sustainable and modern energy for all in 2030 (UN, 2018). While many countries are moving in the right direction, conditions are worsening in others, especially in countries with armed conflict. They are the least likely to benefit from the global energy transition. In addition, people that are forcibly displaced by armed conflict are some of the most vulnerable to energy poverty (Grafham, 2020).

Energy services provided by humanitarian agencies are generally focused on emergency and basic needs provisions. Examples are stove handouts, charcoal rations, solar lantern distribution and diesel generators to power essential camp facilities (Grafham, 2020). However, handing out free products has been found to be unsustainable in camps that have existed for longer. The electricity needs of refugees in camps are best met by formal energy services rather than by free distribution (Bellanca, 2014). Energy services are not recognized as a priority in humanitarian assistance, resulting in poor knowledge, low experience and a fragmented approach (Alonso et al., 2021). In order to address this problem, the Global Plan of Action (GPA) for Sustainable Energy Solutions in Situations of Displacement was launched by UNHCR in 2019, which is in line with SDG 7 (UNITAR, 2018). It says that all refugees and host communities should have Tier 2 electricity access in 2030, which means that each household has access to 50 W of power or 200 Wh of electricity per day. This electricity can provide lighting, air circulation, television and phone charging for four hours during the day and two hours in the evening (Thomas et al., 2021).

In many countries, anti-refugee sentiments are part of the political landscape, resulting in the reluctance of the local government to supply infrastructure or long-term services for displacement camps. A popular narrative is that refugees and IDP put pressure on inflation, wages for local jobs and municipal services such as healthcare and waste management (Lahn et al., 2016). In addition, there is a short-term nature of humanitarian response, lack of funding and lack of comprehensive long-term strategies in many interventions (Alonso et al., 2021). This results in short-term energy delivery, which is very inefficient when people end up staying in the camps for longer (Lahn & Grafham, 2015). Besides, a lack of funding obstructs the development of sustainable energy solutions (Alonso et al., 2021). This is especially notable as Grafham & Lahn (2018) have shown that the average time people live in refugee camps is 18 years.

Access to energy services increases the security and dignity of displaced people. It is essential for lighting, heating, cooking and powering devices, such as radios or cellphones. Energy is also essential for water and sanitation provisions, healthcare services and useful for education and community facilities (Grafham, 2020). However, Lahn & Grafham (2015) estimate that around 90% of people in displacement camps do not have access to electricity. Also, they estimate that around 80% of these people cook with the most basic fuel, wood (Lahn & Grafham, 2015). Sustainable energy services would be able to reduce: indoor air pollution while cooking with wood, skipping meals due to a lack of cooking fuel, trading food for fuel and accidents due to lack of lighting (Grafham, 2020). Albadra et al. (2017) even acknowledge energy as a life or death issue in temporary displacement settings. In addition, energy services enable people to thrive and not just survive, enabling them to build their livelihood (Grafham, 2020).

Currently, camps typically use diesel generators to provide electricity (Alonso et al., 2021). However, diesel generator systems are often oversized, vulnerable to fuel price volatility and create air pollution (Alonso et al., 2021). They are highly dependent on the fossil fuel distribution to the camps and run inefficiently, using 10-30% more fuel. This results in higher costs. Due to poor maintenance, these generators have a lifetime of less than 10 years. Besides, electricity from the grid is often unreliable even when a connection to the network exists (To & Subedi, 2020).

An acknowledged solution is the solar PV (Photo Voltaic) mini-grid. A mini-grid is defined by the Energy Sector Management Assistance Program (ESMAP) as: "Electric power generation and distribution systems that provide electricity to just a few customers in a remote settlement or bring power to hundreds of thousands of customers in a town or city" (ESMAP, 2019). Despite the higher investment cost, solar PV systems have lower running costs and have a lifetime of 20 years. The value of solar systems is demonstrated widely but has shown to be especially effective in fragile or conflict-affected contexts (To & Subedi, 2020). In addition, Alonso et al. (2021) acknowledge the suitability of mini-grids for displacement settings due to high population density, high concentration of businesses and institutions and high consuming anchor loads (energy consumption throughout the day).

Many stakeholders, such as humanitarian agencies, donors and host governments, are increasingly pledging to use more sustainable energy sources in displaced settlements. However, there are still barriers that hinder this development. These include scarcity of data on energy use, lack of in-house technical expertise and comprehensive strategies, high upfront cost, short-term perception of protracted situations, perceived risk of long-term infrastructure investments and regulatory uncertainty around the status of these camps. Persistent favorable policy frameworks and increasing private sector engagement are necessary to finance and manage long-term renewable assets (Alonso et al., 2021). In addition, Thomas et al. (2021) state that giving host communities access to the interventions, matching interventions to the requirements of refugees and host communities, training on energy literacy and ensuring, and adequate maintenance of the installations help to maximize the uptake of sustainable interventions in camps.

1.2. Scientific background

This thesis examines electricity access solutions in refugee settlements, focusing on energy modelling and sustainable mini-grid systems. The literature in this field is rather scarce.

A study from Alonso et al. (2021) looks at the potential of a solar-diesel hybrid mini-grid in the refugee camp of Nyabiheke in Rwanda. The authors use the open-source CLOVER (Continuous Lifetime Optimization of Variable Electricity Resources) simulation and optimization model, designed to support rural electrification in developing countries. They use this tool to compare incumbent diesel generators to sustainable mini-grid designs for humanitarian operations within the camp. A representative load profile is used as input in the CLOVER model based on monitored usage data. They found that the fully renewable system has the highest economic and environmental performance in the long term. However, this requires a high initial investment and a longer payback time. Hybrid solar-battery-diesel mini-grids show to be more cost-effective due to the use of the existing, flexible and reliable diesel infrastructure and the lower expenditures for PV and battery installations.

The study by Cerrada & Thomson (2017) designs a PV mini-grid system for the Bahn refugee camp in Liberia. The authors calculate the PV and battery capacity, electricity distribution and backup diesel generator capacity based on three scenarios: electricity supply for lighting and mobile phone charging of refugees, electricity supply for essential camp services (institutional demand) and a combination of the two. The electrical load profile they used is not based on field-data but on typical load profiles for each type of demand (i.e., households, lighting and a health clinic). The commercial HOMER (Hybrid Optimization of Multiple Electrical Renewables) software is used to derive and validate the technical model. This tool is designed to simulate and optimize hybrid mini-grid designs. They found that the system from the first scenario performs well and is profitable. Scenario 2 is unlikely to be viable. However, financial viability and attractiveness are improved when the household load is added to the institutional load (scenario 3).

The research from Lehne et al. (2016) looks at refugees and IDP in camp and non-camp configurations. The authors focus on gathering and estimating the energy consumption data and corresponding fuel cost for cooking and lighting of households. This can then be scaled up to different sizes of camps and to a global scale. In addition, they mention that solar mini-grids can be used to increase the camps' Tier levels of electricity access. However, they only estimate the cost that this would require and do not focus on the modelling of this mini-grid.

Neves et al. (2021) focus on producing typical energy demand profiles for electricity needs and cooking in refugee camps. The authors distinguish the daily electricity needs per household, based on different Tier levels of electricity access, and the daily electricity needs of infrastructure and camp facilities (institutional load). Consequently, they use the camps population and an average family size of 5 to compute the overall electricity needs of a settlement. The second part of this study focuses on modelling a mini-grid for the Mantapala refugee camp in Zambia using the HOMER software. They compare combinations of PV-wind-biogas-diesel hybrid mini-grids with a baseline scenario of diesel generation. HOMER optimizes these different energy configurations based on Net Present Cost. They found that a hybrid renewable mini-grid with PV-biogas-battery systems can substantially reduce the payback period and the cost of electricity.

1.3. Research gap

Cerrada & Thomson (2017) and Neves et al. (2021) use the commercial software HOMER. This software is not accessible to everyone and is not designed specifically for refugee settlements. It is designed to simulate the mini-grid system for a given location. Alonso et al. (2021) use the open-source CLOVER software. This software is also not designed specifically for refugee settlements but can still be used for this purpose. The CLOVER model requires specific and detailed information about a camp as input. The user has to collect field-data either on actual load profiles or on the amount and type of appliances used in a camp to estimate the electricity demand. Because of this, the model is used to design mini-grid configurations for one specific camp.

It is difficult to estimate the electricity needs in a refugee camp, as there is often low access to electricity among settlements' households. This leads to informal connections and access to neighboring diesel generators and/or grids, which are mostly not monitored in any way (Neves et al., 2021). In the literature, it was seen that the estimation of a camp's electrical demand was done either based on field-data of that camp (Alonso et al., 2021) or based on typical load profiles that were not based on field-data of a refugee camp (Cerrada & Thomson, 2017) (Neves et al., 2021). In addition, it was seen that the electrical demand of camps was scaled up to other camps or to a global level before (Neves et al., 2021) (Lehne et al., 2016). However, when the mini-grid size and corresponding financial indicators are determined, all articles focus on a case study where they use either the CLOVER or the HOMER software.

Baldi (2021) designed the KALO-model in Excel, which can determine the mini-grid size and corresponding financial indicators for any displacement settlement in Sub-Saharan Africa (SSA). It uses field-data (collected in 2020) on the daily load profile of households, businesses and institutions from the Kalobeyei refugee camp in Kenya, where they had a pre-existing mini-grid. The KALO-model takes the load profiles found in Kalobeyei and uses them to create load profiles for other camps, using corrective factors. Only basic input data, such as the population number and the average family size, are needed from these camps to produce camp-specific daily load profiles (i.e., field surveys are unnecessary). With this estimated demand, the required PV and battery capacity are calculated. However, running the Excel model is time-consuming and prone to error, as many cells need to be adjusted manually. This makes it difficult to use for anyone that was not involved in the development of the model (and a manual is not available). Also, the input, calculations and output are unstructured and difficult to find in the model. Therefore, the model is not open source. Lastly, the KALO-model only considers PV-battery configurations, while other technological options, such as hybrid configurations with diesel, could also have a high potential.

1.4. Research aim

Baldi (2021) started filling the gap in the literature by producing a pre-feasibility model that can estimate the camp-specific daily load profile, determine the PV-battery mini-grid size and compute financial indicators for all refugee camps in SSA. However, there are many areas of improvement for the KALO-model, on which this research will focus. The following research aim is set for this research, followed by two sub-aims:

Building an open-source pre-feasibility planning model in Python to compute the mini-grid's size for displacement settlements in Sub-Saharan Africa and to compute relevant techno-economic indicators to evaluate alternative configurations, based on scarce input data.

Sub-aim 1: Reproduce the parts of the KALO-model that produce load profiles of households, businesses and institutions based on field-data, compute the PV and battery capacity to meet the demand and determine the Upfront Cost and the Levelized Cost of Electricity, implement small improvements and validate it.

Sub-aim 2: Implement larger improvements on the Python model, regarding different technological options for electricity access, such as a hybrid system with diesel and connecting the camp to the national electricity grid, and the inclusion of electricity demand for clean water production.

1.5. Scientific relevance

The model built in Python should be improved in terms of structure, modularity, computation time and user-friendliness compared to the KALO-model from Baldi (2021). The latter improvement makes it easier to use and share the model with other researchers. Adding more technological alternatives for the mini-grid will enable to compare the different options in terms of required capacity and cost. Furthermore, the model can be used to compare technological and financial indicators of different camps and it can indicate the scale for providing mini-grids to all settlements. The pre-feasibility model is useful for humanitarian agencies such as UNHCR to see which camps have a high potential for cost-effective mini-grids. This way, they can create pipeline projects and programs per country, make a planning and make implementation plans. This research contributes to SDG 7 and the GPA for Sustainable Energy Solutions in Situations of Displacement. It can help identify settlements with a high potential for mini-grid implementation in terms of techno-economic indicators. It contributes to the field of energy modelling of sustainable mini-grids for refugee settlements in developing countries.

2. Methodologies

The methodology of this research follows the sub-aims described in Section 1.4. A schematic overview of the methodology of this research is given in Figure 1. In the next paragraph, a short introduction to Python will be given. After that, the steps from Figure 1 will be explained. All the data used for this research has been gathered by Baldi (2021) or other researchers and was therefore reused. There were no ethical issues relating to data collection and handling.

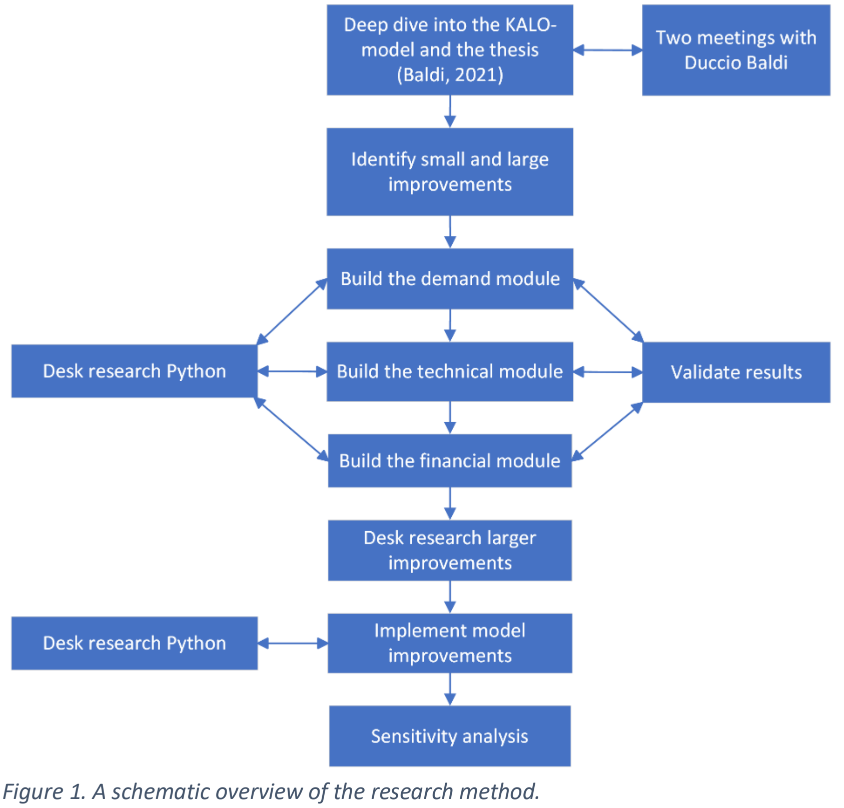

Figure 1. A schematic overview of the research method.

2.1. Python introduction

Python is an open-source programming language. It has many applications such as web and internet development, scientific and numeric computing, software development and business applications (PSF, n.d.-b). It is widely used in the scientific community because of its large and expanding number of libraries, which is seen as an advantage compared to other programming languages such as R and Matlab (Nelli, 2015). An Integrated Development Environment (IDE) is needed to use Python. For this study, Spyder (Scientific Python Development Environment) version 5 was used, as it is suitable for scientific purposes and has been used before by the author at Utrecht University. Anaconda was installed to use Python 3.9, which was the most recent version at the time of this study. Appendix 1 elaborates on the concepts and features of Python, which are used in this research. Lastly, the author's experience in Python and the advantages of this program over others resulted in the choice to use Python.

2.2. Building the model

The first part of the research required a "deep dive" into the KALO-model produced by Baldi (2021) in Excel, which is called KALO 1.0, and the thesis (Baldi, 2021). The goal was to reproduce the Excel model in Python using the same formulas and assumptions. Therefore, all input data used and calculations made to build the three modules were gathered from KALO 1.0 (Baldi, 2021). In addition, multiple emails were exchanged and two meetings were held with Duccio Baldi, the creator of the KALO-model, to clarify the structure and content of the model.

From this "deep dive", small and large model improvements were identified. The next step was to build the Python model's first version, called KALO 2.0. Small improvements were incorporated in KALO 2.0 and entailed re-resigning the model structure and sequence of computations. Larger improvements were implemented later. This approach was chosen not only because of the transposition to Python but also because it prevented replicating a structure that was not logical. Nevertheless, keeping the same formulas and assumptions allowed to validate the results from KALO 2.0 with KALO 1.0. This prevented mistakes that would otherwise have been difficult to find and solve. Validating the results was important for each of the three modules and was done for every type of result. This was an interactive process, as is shown in Figure 1. Doing desk research on Python features and on how to implement small model improvements was also part of the interactive process of building the three modules. When a problem was encountered during the programming process, grey literature was consulted to solve these problems.

When the model of Baldi (2021) had been reproduced in Python and the result matched, the research moved on to the larger model improvement part. Larger improvements were identified earlier and used at this research stage. The first step was doing desk research on existing models or (parts of) codes that could be used. When something is already available, it might be easy and fast to implement this improvement and it could prevent doing work that someone else has done before. The following step was implementing the improvements and ensuring the model ran properly. At the same time, a Python desk research was carried out about how these improvements could be implemented in the Python code. This is in line with Figure 1.

A sensitivity analysis was carried out when the model improvement part was finished. The sensitivity analysis studied the effect of the O&M cost, the customer connection cost and the discount rate on the LCOE, just as was done by Baldi (2021). The analysis was expanded by looking at the effect of diesel fuel prices and the project lifetime on the LCOE. A sensitivity analysis was relevant to see which parameters greatly affected the model outcomes. It was done at this research stage to see the model improvements' effect.

Lastly, it is important to point out that this research focused on building the model, not on data collection or the update of data used by Baldi (2021). The goal was to build the Python model so that it would be easy to add or change data in the future.

2.3. The KALO-model

This section gives a general explanation of the KALO 1.0 Excel model. The results of the "deep dive" are given in Section 3.2. The KALO-model was built in Excel, containing nine different sheets. However, it became clear from Baldi (2021) that it contains three main parts. The first part, the estimation of a camp's electricity demand of a camp, is described in Figure 2. The goal is to estimate the daily load profile of households, businesses and institutions. A load profile contains the hourly demand for electricity for one day and is, therefore, a 1x24 vector. Summing these three profiles results in the camp's total daily load profile. The inputs required are the load profiles of households, businesses and institutions gathered from field research in the Kalobeyei refugee camp in Kenya (Baldi, 2021). This refugee camp hosts around 36,000 people and consists of three zones. One of these zones had a pre-existing mini-grid.

Five corrective factors (CFs) are used to linearly transform the Kalobeyei load profile into a camp-specific load profile (explanation of CFs can be found in Baldi (2021) and Appendix 2.1). The only camp-specific input data necessary are the Population hosted in the camp and the Average family size. If available, the number of households, businesses and institutions are also used as input, resulting in more accurate load profiles. This data was collected by Baldi (2021) for 288 refugee sites in SSA. The camps were identified by their geographical location. The main output is a camp-specific daily load profile for households, businesses and institutions. The sum of these 24 hourly values gives the daily energy demand of a camp in kWh/day. This daily load profile is the same for every day of the starting year, year 1, not considering demand growth. Another daily load profile is calculated for year 6, considering 10% demand growth per year (Annual demand growth) for five corresponding years (Demand projection time frame). After year 6, it is assumed that the demand will stay constant (Baldi, 2021).

There are multiple demand scenarios that the user can define. First, there are Baseline, Tier 2 and Tier 3 scenarios. The Baseline scenario is the one described above. The Tier scenarios are based on the World Bank's multi-tier framework for households' electricity access, ranging from Tier 0 (no electricity) to Tier 5 (8200 Wh) (Neves et al., 2021). In the Tier 2 and Tier 3 scenario, households' electricity demand is increased to 200 Wh and 1000 Wh, respectively. In addition, there are two electrification coverage rate (ECR) scenarios. The ECR defines which percentage of the total number of households, businesses or institutions in the camp will be connected to the mini-grid. The ECR of businesses and institutions is assumed to be constant at 100%, while the ECR of households can be changed to either 80% or 100% (Baldi, 2021). The ECR of households is not continuous because of lacking data regarding the trend adjustment factor, which is CF3, defined by Baldi (2021).

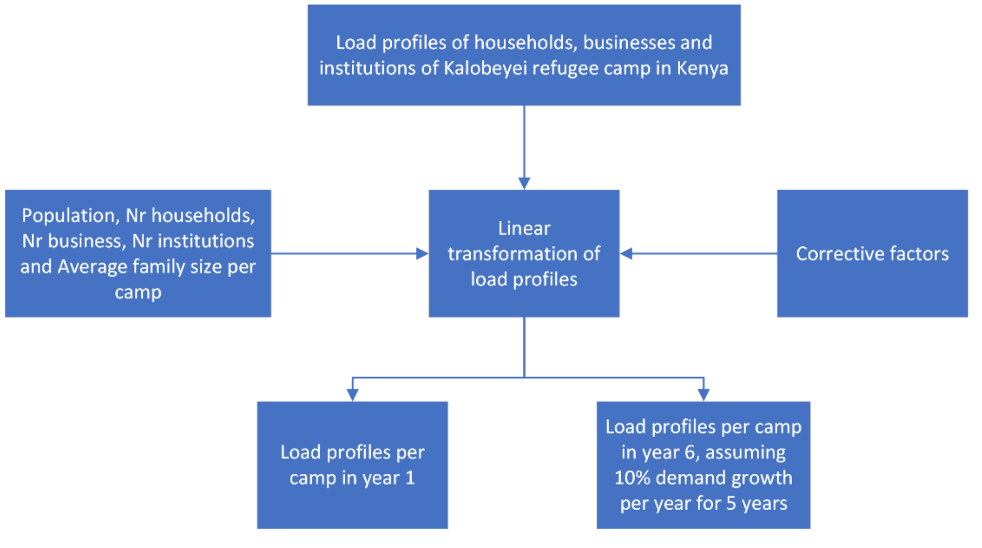

Figure 2. Description of the demand estimation of refugee camps in the KALO-model.

When the daily energy demand of a camp in year 6 is known, the solar PV and battery capacity can be scaled to this demand. This means that the installations are oversized in the first few years compared to the electricity demand. However, using this approach, the installations can still cover the demand after year 6. The only camp-specific input data required for these calculations are the average daily Peak sun hours.

The demand and technical parts output is used as input for the financial part. The goal of the financial part is to calculate the project's upfront cost, followed by calculating the Levelized Cost of Electricity (LCOE). Country-specific input data is needed for this, including national electricity tariffs, exchange rates and national inflation rates. For the upfront cost, which are investments made at the start of the project, generation, distribution and other upfront costs are considered. For the LCOE calculation, multiple yearly costs are calculated, such as Operation and Maintenance (O&M), insurance, Value Added Tax (VAT), land lease, interest, tax and replacement cost. Together with the upfront cost and the yearly electricity generation by the system, the yearly cost are used in the LCOE calculation, returning a value in USDc/kWh. A discount rate of 10% and a simulation period of 20 years are used (Baldi, 2021). The resulting LCOE values can be compared between different camps and between different demand scenarios.

3. Results Part I: KALO 2.0 - model reproduction and small improvements

The results chapter starts with Section 3.1, which gives an overview of the areas of improvement identified based on the “deep dive” into KALO 1.0 and the thesis (Baldi, 2021). After that, a description of the Python model, KALO 2.0, is given in Section 3.2 for each of the three key modules. This description includes the equations and assumptions used by Baldi (2021) obtained during the “deep dive”. In addition, this description includes how the model is built in Python, explaining which Python functions and features are used. Section 3.3 gives an overview of the small improvements made in KALO 2.0. This chapter ends by comparing the results between KALO 2.0 and KALO 1.0.

3.1. Model improvements

The three parts of the KALO-model described in Section 2.3 are not logically structured in Excel. Input data, calculations, output and user input requirements are not separated and defined properly. The user has to make manual adjustments in multiple sheets to get the results of just one camp. Formulas are hidden in cells and there is no clear description of the calculations. In addition, a sensitivity analysis can only be run manually, taking much time. In terms of small model improvements, the goal is to build KALO 2.0 in Python, achieving a better structure, a shorter running time and a lower sensitivity to errors.

Seven areas of improvement were identified for the larger model improvements, based on Baldi (2021) and Baldi et al. (2022). These are grouped based on input data and the three parts of KALO 1.0:

- Input data
    - The input data, such as population per camp, is from UNHCR2020 and could be updated to more recent data.
- Demand module
    - The characterization of electricity demand was done in a linear and simple way. Estimating the electricity demand could be done more realistic, where more heterogeneity of households, businesses and institutions is included.
    - The existence of a mini-grid can improve clean water production in the refugee settlements, which would either reduce the energy demand for other uses or require the installations to be scaled to the increased electricity demand. This could be added to the model.
- Technical module
    - There is no estimation in the technical module on the length of distribution cables necessary to connect all consumers. In addition, the upfront cost of distribution in the financial module can be adjusted to USD/km instead of USD/connection.
    - The model only considers mini-grids with solar PV and battery installations. Other technological options could be explored, such as hybrid PV-battery-diesel systems. It could also be an option to incorporate a scenario of connecting the camps to the national electricity grid when it is available, reliable and sustainable.
- Financial module
    - Financial parameters, such as the investment costs of certain technologies, are not differentiated per country, while in reality, this would be the case.
    - Affordability data generated by Baldi (2021) could be incorporated. This data was never used in his research, but it is available and valuable.

3.2. Description of the Python model

The model created in Python, KALO 2.0, has three key modules: a demand, a technical and a financial module. It also contains a sensitivity analysis module, which will be discussed at the end of Chapter 0.

Each of the three key modules has the same structure:

0. User input: to define the demand scenario (only in the demand module)
1. Constants
2. Input
    a. Import of libraries
    b. Import of constants and functions from other modules
    c. Import of data from CSV files
3. Calculations for the output
4. Functions that define how to run the code for one camp and all camps
5. Definition of questions to ask the user: whether to run for one camp or all camps

If the user wants to run the Python model, the first step is to define the demand scenario at the top of the demand module, in the Editor Pane. This is displayed by the red arrow in Figure 3. Here, the user has to define for which electricity access level to run (= scenario_name), which is either Baseline, Tier 2 or Tier 3, and for which Electrification Coverage Rate (ECR) of households (= ECR_hh), which is either 80% or 100% (see Section 2.3). The next step is to press the green play button, which can be found at the top of the Python program. It is displayed by the red circle in Figure 3. This executes the code from the Editor Pane. A question pops up in the Python console, which is displayed by the blue arrow in Figure 3. Here, the user must reply to the questions asked, followed by pressing Enter on the keyboard. The model asks the user whether the computations are to be done for one camp or all camps. Only when the user enters to run for one camp, two follow-up questions are asked, which are to enter the camp name and corresponding zone. When all questions are answered, the code is executed and the results are printed either to the console (run for one camp) or to a CSV file (Comma-separated values) (run for all camps). Note that the steps from pressing the green button onwards must be repeated for running each module.

When doing calculations for one camp, the three modules can be run individually. However, it is important to run the demand module before running the technical module and to run the technical module before the financial module, when doing calculations for all camps. This is due to the fact that the technical and financial modules use the output CSV file created in their previous module(s) as fixed input. The following paragraphs explain the code written in the Editor Pane for each of the three key modules.

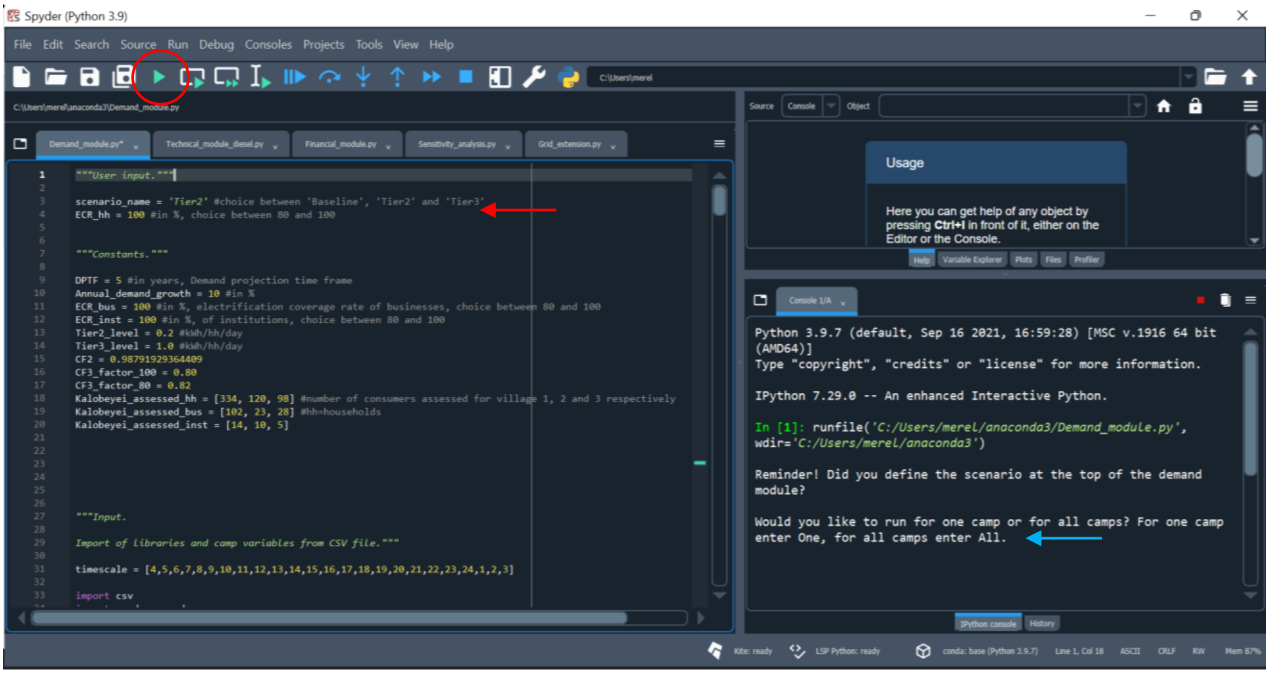

Figure 3. The Spyder environment in which Python is used. The circle and arrow specify the only places where input is required from the user.

3.2.1. Demand module

The user-defined input explained in Section 3.2 is followed by the definition of "constant numerical values" used in the demand module and by creating a dictionary with the "camp inputs". The constant numerical values are reported in Table 1 and their use is explained in Baldi et al. (2022) and Appendix 2.1.

Table 1. Constants for the demand module.

Constant	Value	Unit
Demand projection time-frame	5	Years
Annual demand growth	10	%
ECR businesses	100	%
ECR institutions	100	%
Tier 2 level	0.2	kWh/hh/day
Tier 3 level	1.0	kWh/hh/day
Tier 2 factor	0.9879	- (fraction)
CF 3 factor 100%	0.80	- (fraction)
CF 3 factor 80%	0.82	- (fraction)
Kalobeyei assessed households	[334, 120, 98]	#
Kalobeyei assessed businesses	[102, 23, 28]	#
Kalobeyei assessed institutions	[14, 10, 5]	#

As for the camp-related input data, the approach used in KALO 1.0 needs to be restructured. Therefore, a CSV file called "Variables.csv" is created, which contains information on the following 13 points for each camp: Country, Camp name, Zone of the camp (if the camp is divided into multiple zones), Population hosted in the camp, Number of Households, Number of Businesses, Number Institutions, Average family size per household, Peak sun hours, Existing PV capacity (kWp), Existing battery size (kWh), Existing diesel generators (kW) and Distance to the national grid (km). These data were collected via desk and field research in 2020 (Baldi, 2021) and can now be easily accessed via the file "Variables.cvs".

This CSV file is an Excel sheet converted to CSV. As of today, it contains 288 rows with on each row information on one camp/zone. Python reads this file using the csv library and a “for” loop is used to loop over all rows of the CSV file. A dictionary is created with 288 key-value pairs. The “key” is the camp name and its zone, and the “value” is a list of all parameters from that row of the CSV. Now the data is stored in Python and can be used in the rest of the code. Data in this CSV file can easily be updated and new camps can be added. When extra information is added to the CSV file (an extra column in the Excel file), this has to be defined in the “camp_input_par” function described below.

From this input data, additional “constant numerical values” are computed to be used in estimating the camp’s electricity demand. These values are also referred to as corrective factors (CF) for businesses and institutions: the CF_{bus} and CF_{inst}. The code takes all available values from the “Variables.csv” file about the number of businesses (Nr_{bus_i}) and institutions (Nr_{inst_i}) and calculates the corrective factors. Thus, they change when data is deleted, changed or added. CF_{bus} and CF_{inst} are defined as:

$$CF_{bus}(CF_{inst}) = \frac{\sum_{i=1}^{x} \frac{Nr_{bus_i}(Nr_{inst_i})}{Nr_{hh_i}}}{x} \qquad \text{Eq. 1}$$

where x is the amount of camps for which the number of businesses or institutions is known.

The resulting values for CF_{bus} and CF_{inst} are 0.0507 and 0.0059, respectively. The function “camp_input_par” defines the input parameters of a given camp, using the dictionary that was created before. This dictionary serves as a look-up table. A camp is defined by its camp ‘name’ and ‘zone’ and these are therefore variables of the Python function. When the number of households is known from field or desk research, the value included in the “Variables.csv” file is used. When this value is unknown, the Population is divided by the Average family size. Similarly, when the number of businesses and institutions are known, these are used. When these are unknown, the Number of households is multiplied with CF_{bus} to calculate the amount of businesses and with CF_{inst} to calculate the number of institutions. The “camp_input_par” function returns a dictionary, which makes it easy to access a specific value belonging to a camp.

After that, a CSV file “Kalobeyei.csv” is imported. This file contains the measured hourly load profile of Village I and the estimated hourly load profile (kW) of Village II and III of the Kalobeyei camp in Kenya (Baldi, 2021) – actual field-data from 2020. Each hour (and row in CSV file) is added as a list into one big list, using a “for” loop, to store the data in Python. The data is structured as is given in Table 2.

Table 2. Structure of the "Kalobeyei.csv" input file. Values are given in kWh.

	Hh V1	Hh V2	Hh V3	Bus V1	Bus V2	Bus V3	Inst V1	Inst V2	Inst V3
04:00	386.40	112.05	60.71	85.45	14.15	25.82	545.25	389.70	288.81
05:00	253.42	112.05	83.53	38.84	14.15	17.21	213.89	263.88	161.39
Etc.									

The “kalobeyei_variables” function defines that the first three values of each hour belong to households (orange cells from Table 2), the second three to businesses (blue cells) and the third three to institutions (yellow cells), again returning a dictionary. This is defined as the trend’s load profile per type of consumer, $LP_{Trend,cons}(t)$. The last part of the input is the calculation and definition of CF1 and CF4. The corrective factors are explained in Baldi (2021) and specified further in Appendix 2.1.

The output part of this module calculates the load profile per type of consumer in year 1 and year 6. This is done using the corrective factors defined by Baldi (2021).

The load profile per type of consumer in year 1, $LP_{cons,y1}(t)$ (kWh), is defined by:

$$LP_{cons,y1}(t) = average(LP_{Trend,cons}(t)) * \frac{CF1}{1000} * CF2 * (1 - CF3) * CF4 * CF5$$ *Eq. 2*

The load profile per type of consumer in year 6, $LP_{cons,y6}(t)$ (kWh), is computed as:

$$LP_{cons,y6}(t) = LP_{cons,y1}(t) * (1 + ADG)^{DPTF}$$ *Eq. 3*

where *ADG* is the annual demand growth and *DPTF* is the demand projection time frame (see Table 1).

In addition, the total load profile is defined for each of these two years, which is the sum of the three load profiles for households, businesses and institutions.

The daily energy demand function returns two values. The first value does not consider the demand covered by an existing mini-grid (in case there is one), while the second one does. The daily energy demand for which the demand of an existing mini-grid is subtracted is called the effective demand. In addition, the module calculates the consumption share and the number of connections per type of consumer. These are necessary for the calculation in the financial module. Their equations are given in Appendix 2.1.

After that, there are two functions of which one defines how to run the code for one camp and the other defines how to run the code for all camps. For one camp, the daily energy demand and effective demand in years 1 and 6 are printed in the Python console. For the output of all camps, the results are printed to a CSV file, using the Pandas library. A "for" loop is used to loop over all camps and to return corresponding results. Lists per output type are created that contain the output values for all camps. These lists form columns in the CSV file. The output indicators are: Energy demand year 1 (kWh), Effective energy demand year 1 (kWh), Energy demand year 6 (kWh), Effective energy demand year 6 (kWh), Total hourly load profile year 6 (kW), Consumption share households, Consumption share businesses and Consumption share institutions. A separate CSV file is created when the module is run for a different demand scenario, with the name "output_file_<scenario_name>_<ECR_hh>.csv".

The questions to ask the user when he/she presses play are defined at the bottom of the code. It starts with a reminder to the user if he/she defined the demand scenario (as seen in Figure 3). Then the question is defined whether the computations are to be done for one camp or all camps. Only when the user enters to run for one camp, two follow-up questions are asked, which are to enter the camp name and corresponding zone. This is the same piece of code in each of the three key modules.

3.2.2. Technical module

This module starts with constant numerical values at the top (see Table 3), followed by the import of several inputs. The function "camp_input_par" is imported from the demand module, which means it can also be used in this module. Furthermore, from the demand module, the scenario name and the ECR or households are imported. The last six constants from Table 3 are needed for calculating the emission factor later in this module. The emission factor is needed to calculate the avoided emissions of the sustainable mini-grid compared to a reference diesel generator. More information on this can be found in Appendix 2.2.

Table 3. Constants for the technical module.

Constant	Value	Unit
System losses	25	%
Battery efficiency	80	%
Battery depth of discharge	90	%
Reserve margin	30	%
Load by battery or solar high	0.7	- (fraction)

Load by battery or solar low	0.3	- (fraction)
Yday	365	Days in a year
Diesel generator size	75	kW
Load factor	50	%
Conversion US gal to liter	3.785	Liter/US gal
Diesel density	0.85	Kg/liter
Net caloric value diesel	43	TJ/Gg (1 Gg = 1000 t)
Emission factor diesel	74100	Kg CO2/TJ

For the output, the PV system size and the battery size are calculated (Baldi, 2021). The energy demand in year 6 is used for this, not the demand in year 1, nor the effective demand. When there is an existing mini-grid, the existing PV and battery size are subtracted at the end of this calculation. The demand in year 6 is used because the PV and battery installations are scaled to meet the demand, including 5 years of growth.

Table 4 gives an overview of the fractions of the demand covered by solar PV and batteries during the day. The solar PV can only be used during the sunlight hours, which is from 09:00 to 17:00. During sunrise and sunset, the demand is covered by both solar PV and batteries, and during the dark hours, only the batteries are used, which is from 19:00 to 07:00 (Baldi, 2021).

Table 4. The fraction of solar PV and batteries used at specified hours of the day, to cover the demand.

Time (hour starting at)	**Solar PV**	**Batteries**
7:00	30% (Load by battery or solar low from Table 3)	70% (Load by battery or solar high from Table 3)
8:00	70% (Load by battery or solar high from Table 3)	30% (Load by battery or solar low from Table 3)
9:00-16:00	100%	0%
17:00	70%	30%
18:00	30%	70%
19:00-6:00	0%	100%

The *PV system size (kWp)* is defined by:

$$PV\ system\ size = \frac{SUM([LP_{tot}(t)]) * (1 + system\ losses) * (1 + reserve\ margin)}{PSH} - kWp\ PV\ existing\ grid \quad \text{Eq. 4}$$

where the total load profile, $LP_{tot}(t)$, defines the demand of households, businesses and institutions together at hour *t* (in kWh) and PSH are the Peak sun hours (in kWh/m^3). $[LP_{tot}(t)]$ is a vector of 1x24 defining the daily load profile.

The *Battery size (kWh)* is defined by:

$$Battery\ size = \frac{SUM([B(t)])(1 + system\ losses) * (1 + reserve\ margin)}{Battery\ efficiency} * (1 + (1 - depth\ of\ discharge)) - \ kWh\ Batteries\ existing\ grid \quad \text{Eq. 5}$$

and the demand to be satisfied by batteries at hour *t*, $B(t)$ (kWh), is defined by:

$$B(t) = \begin{cases} LP_{tot}(t), & if\ 7{:}00 > t > 19{:}00 \\ LP_{tot}(t) * 0.7, & if\ t\ =\ 7{:}00\ and\ t = 19{:}00 \\ LP_{tot}(t) * 0.3, & if\ t = 8{:}00\ and\ t = 18{:}00 \\ 0, & Otherwise \end{cases} \quad \text{Eq. 6}$$

$[B(t)]$ is a vector of 1x24 defining the demand to be satisfied by batteries at every hour of the day.

The peak sun hours used in the calculation for the PV capacity define the average daily solar irradiation in kWh/m^3 (averaged over a year). They are used as fixed input from Baldi (2021) for each camp. More information on the peak sun hours calculation can be found either in Baldi (2021) or Appendix 2.2. The reserve margin increases the capacity of both solar PV and batteries, allowing for extra electricity generation that can be used in case of system failures or other issues. The reserve margin can be a percentage higher than 100%, which means that the system can produce electricity to cover the demand for an extra day or more.

In addition, the yearly avoided emissions are calculated. The emission factor is 0.93 tCO_2/MWh and it is assumed that the emissions of the solar-battery system are zero (Baldi, 2021).

The yearly avoided emissions, $Avoided_{em(year)}(t\ CO_2)$, are computed by:

$$Avoided_{em(year)} = EF * \frac{eff_{demand_{year}}}{1000} * Yday \quad \text{Eq. 7}$$

where *EF* is the emission factor, $eff_{demand_{year}}$ is the effective demand in years 1 or 6 and *Yday* are the amount of days in a year.

At the end of the code, the functions to run the module for one camp and all camps are given. To run for one camp, the PV capacity, battery capacity and avoided emissions in year 6 are printed to the console. To do this, the functions that compute the daily energy demand in years 1 and 6 and the daily load profile in year 6 are imported from the demand module. This is done because their outcomes are needed in the calculation of the PV and battery capacity and the avoided emissions.

To run the code for all camps, the output of the demand module is used as fixed input in the technical module. For this, Python opens and reads the CSV file that has been produced in the demand module. A dictionary is created in which each row (and thus each camp) is represented by a key-value pair, using a "for" loop. The function "demand_input_par" defines the input parameters belonging to the camp called in the function, returning a dictionary. This is done because using the functions directly from the demand module (as is done to run for one camp) results in a long computational running time. The output indicators of the technical module are: PV size (kWp), Battery size (kWh) and Avoided emissions year 6 (t CO_2). The output for all camps is added to the output file of the demand module.

3.2.3. Financial module

The module starts with the constants numerical values from Table 5. An explanation on these constants and how they are used is given in Baldi (2021), Baldi et al. (2022) and Appendix 2.3. In addition, several inputs are imported. The functions "camp_input_par" and "nr_connections" are imported from the demand module, together with constants such as the ECR of businesses and institutions, the demand projection time frame, the annual demand growth, the scenario name and the ECR of households.

Table 5. Constants for the financial module.

Constant	Values used in KALO 1.0 (Baldi, 2021)	Unit
For upfront cost calculation		
Inverter to PV ratio	1.2	-
Project cost existing mini-grid projects	6200	USD/kWh
Start substation	2000	Nr households
For LCOE calculation		
Simulation period	20	Years
Replacement time batteries and PV inverter	10	Years
Replacement time PV modules and other assets	20	Years
VAT rate	14	%
TAX rate	25	%
Insurance rate	1	%
Interest rate debt	8	%
Project cost financing - debt	2	%
Debt repayment period	11	Years
Land lease cost	0	USD/year
Connection fee consumer	5.4	USD/connection
Yearly cost reduction PV modules	3	%
Yearly cost reduction PV inverter	3	%
Yearly cost reduction batteries	4	%
Yearly cost reduction other assets	0	%
Conversion inflation to devaluation	0.5	-
Built connections households year 1	40	%
Built connections households year 2	70	%
Generation hours per day	95	%

A CSV file is created to restructure the semi-fixed input from KALO 1.0. It is called "Semi-fixed_input.csv" and contains the following semi-fixed parameters for each country: national electricity tariffs for households, businesses and institutions (national currency/kWh), inflation rates of 4 years (%), the exchange rate (national currency/USD), mini-grid project cost (USD) and the weighted average cost of capital (WACC) (%). These values are the same for all camps in the same country. Each country occupies one row in the CSV file. A dictionary is created with the country name as "key" and the corresponding row of the CSV file in a list as "value". The country-specific WACC was computed by Baldi (2021) based on the equity rate of return and debt interest rate in that country. This WACC is used later as a discount rate in the LCOE calculation. As of today, only for Kenya there is a value known for the mini-grid project cost. This value is used in calculating the Other upfront cost (see Table 6). For the countries where this value is unknown, the Project cost of existing mini-grid projects of 6200 USD/kWh is used (see Table 5) (Baldi, 2021).

The first part of the financial model is to calculate the upfront cost, which are investments that must be made to build the mini-grid. They are divided into generation, substation, distribution and other upfront costs. The distribution of these costs is displayed in Table 6. The values used for the upfront cost calculation are specified at the top of the code, together with the constant numerical values mentioned in Table 5. The number of connections belonging to the existing mini-grid (EMG), in case there is one, is needed in the calculation of distribution upfront cost and is given in Appendix 2.3.

Table 6. Upfront cost that occur as investments at the start of the project.

Input	Value	Unit	Equation	
Generation Upfront cost (USD)				
PV modules	320	USD/kWp	$= value * PV\ system\ size$	*Eq. 8*
Panel frames	140	USD/kWp	$= value * PV\ system\ size$	*Eq. 9*
PV inverter	110	USD/kWp	$= value * \frac{PV\ system\ size}{Inverter\ to\ PV\ ratio}$	*Eq. 10*
Solar monitoring system	600	USD/ System	$= value * 1$	*Eq. 11*
Batteries	230	USD/kWh (nominal)	$= value * Battery\ size$	*Eq. 12*
Accessories	50	USD/kWh (nominal)	$= value * Battery\ size$	*Eq. 13*
Security & civil works	80	USD/kWp	$= value * PV\ system\ size$	*Eq. 14*
Substation Upfront cost (USD)				
Substation	1000	USD/kWp	$= value * PV\ system\ size$ Only if $Nr_{hh} > Start\ substation$	*Eq. 15*
Distribution Upfront cost (USD)				
Customer connection	80	USD/ connection	$= value * \begin{pmatrix} hh * ECR_{hh} + bus * ECR_{bus} \\ +inst * ECR_{inst} - Nr_{con}\ EMG \end{pmatrix}$	*Eq. 16*
Low voltage distribution	145	USD/ connection	$= value * \begin{pmatrix} hh * ECR_{hh} + bus * ECR_{bus} \\ +inst * ECR_{inst} - Nr_{con}\ EMG \end{pmatrix}$	*Eq. 17*
Other Upfront cost (USD)				
Logistics and project management	10	% of investment cost	$= value * Project\ cost\ existing\ mini\ grid\ projects * PV\ system\ size$	*Eq. 18*
Contingency	5	% of investment cost	$= value * Project\ cost\ existing\ mini\ grid\ projects * PV\ system\ size$	*Eq. 19*

After the upfront cost calculation, the module continues with the calculation of the LCOE (Eq. 20). The LCOE formula in Python contains a "for" loop that calculates the yearly cost for every year in the simulation period and discounts this value to the present. For a standard run of the financial module, a discount rate of 10%, O&M cost of 1% (of total upfront cost) and customer connection cost of 80 USD/connection are used. These parameters are variables (and thus remain undefined until the end of the code) in the financial module, which makes it possible to adjust them easily for sensitivity analysis later on.

Two types of LCOE can be generated as output: LCOE-all and LCOE-GenOnly. The LCOE-all takes all upfront cost into account, while the LCOE-GenOnly takes only generation and other upfront cost into account, excluding distribution and substation cost (Baldi, 2021). This approach makes it easier to compare LCOE values with existing literature, as they often focus on the generation part of the LCOE.

The *LCOE (USDc/kWh)* is defined by:

$$LCOE = \frac{Upfront_0 + \sum_{i=1}^{t} \frac{R_z + O\&M_i + F_i}{(1+r_n)^t}}{\sum_{i=1}^{t} \frac{Eg_i}{(1+r_n)^t}} * 100 \qquad \textit{Eq. 20}$$

where $Upfront_0$ includes the Upfront Cost for generation, substation, distribution and other cost (USD);

R_z is the replacement cost of PV inverters, batteries and PV modules at year z (USD);

$O\&M_i$ represents the operation and maintenance cost (USD);

F_i are the financial expenditures, including insurance, Value Added Tax, interest for debt, tax and land lease (USD);

r_n is the discount rate (%);

Eg_i represents the electricity generated by the PV system per year (kWh).

The equations that are used to calculate the replacement cost, yearly cost and electricity generation mentioned above are given in Appendix 2.3.

At the end of the code, the functions and commands to run the code for one camp and all camps are given, just as in the other modules. To run for one camp, multiple functions are imported from the demand and technical module, such as the daily energy demand in year 1, the consumption share per type of consumer and the functions to compute the PV and battery size. The results are printed to the console. To run for all camps, the CSV file created at the end of the technical module is used as fixed input in this module and is handled the same as in the previous module.

The output indicators are: Upfront cost (USD), LCOE-all (USDc/kWh), LCOE-GenOnly (USDc/kWh) and LCOE-WACC (USDc/kWh). For the calculation of the LCOE-WACC, the country-specific WACC is used instead of the general discount rate of 10%. This is done to make the LCOE value more specific for the camp's location. These output indicators are added to the CSV file of the demand and technical module. The result is a CSV file with the output indicators of the three modules on one row for each camp.

There is also an option in the financial module to include an increase in the electricity tariff that the consumers have to pay. This percentage can be specified for each consumer separately. Also, the user can specify after how many years the tariff is increased, with a minimum of 5 years (Baldi, 2021). In addition, there is an option to include an increase in the O&M cost, with a user-specified percentage per year (Baldi, 2021). At this moment, they are both set at zero.

3.3. Small improvements compared to KALO

The previous paragraphs have described the Python model. While programming, small improvements were made in terms of content, structure and user-friendliness, which will be discussed below.

3.3.1. Content improvements

The first content improvement discussed below relates to the demand module, while the others relate to improvements in the financial module.

The KALO-model 2.0 was adjusted so that it works for any value of the ECR_{hh}, ECR_{bus} and ECR_{inst}. In KALO 1.0 it was only possible to use an ECR of 80 or 100%. To solve this, it was decided to make CF3 fixed at 82%, instead of varying it between 80 and 82% for an ECR of 100 and 80% respectively. This corrective factor adjusts for the fact that the Kalobeyei refugee camp (from which field-data on load profiles is collected) was already partly connected to a mini-grid at the time of the field-data collection. Because of this, it is expected that the initial demand of consumers in other camps will be lower, as demand is expected to increase in the first years after access. For an ECR of 40%, it was found in KALO 1.0 that CF3 corresponds to 86%. Because the percentages corresponding to CF3 were based on assumptions made by Baldi (2021), the middle value of 82% was chosen for all values of the ECRs.

KALO 1.0 contained a minor error relating to the calculation of depreciation in the financial module. When an asset has a replacement time of 10 years, it is fully depreciated at the end of year 10. In year 10, a new investment is necessary to replace the asset. This asset is again fully depreciated after 10 years, which is at the end of year 20. However, in KALO 1.0 the replacement asset was depreciated faster than 10 years, because a wrong value for depreciation was used. This was corrected in KALO 2.0.

The solar monitoring system cost of 600 USD was missing in the LCOE calculation in KALO 1.0. This cost was recognized in the upfront cost calculation, but was forgotten in the Excel sheet used for the LCOE calculation. This was corrected in the Python model.

KALO 1.0 used multiple costs and prices relating to the connection of consumers to the mini-grid:

- A customer connection cost of 80 USD/connection in the upfront cost,
- *A cost of connection of 5.4 USD/connection in year 1*
- A connection fee of 5.4 USD/connection (as revenue) in year 1

In consultation with Baldi (2021), it was decided to remove the cost of connection of 5.4 USD/connection (the *italic* bullet from above) from the model. The investor pays once to connect the consumer, which is included in the upfront cost. Afterward, the consumer has to pay a fee for this connection, which is 5.4 USD/connection, received as revenue for the project.

Another small error was found. The financial module of KALO 1.0 used the *daily* energy demand in years 1 and 6 from the demand module as fixed input. This energy demand is specified for the defined ECR of households. In the calculation of the *yearly* demand in the financial part of the model, another multiplication was done with the ECR of households. This was seen to be double. Therefore, the latter multiplication was left out in KALO 2.0.

KALO 1.0 defined that a substation is included when the number of households is higher than 2000. This definition is correct for an ECR_{hh} of 100%, as the number of households connected equals the number of connections for households. However, for an ECR_{hh} of 80, the number of households is not equal to the number of connected households. Therefore, the Python model assumes that a substation is included when the *number of connections for households* is higher than 2000.

Lastly, KALO 2.0 gives the option to include land lease cost either as an upfront or a yearly cost. At this moment, the yearly land lease cost are assumed to be zero (Baldi, 2021). However, additional data collection could lead to the inclusion of these costs in the model.

3.3.2. Structure and user friendliness

The Python model uses a clear structure with three main modules. There is one place where the scenario has to be defined and no other manual changes need to be made. The user only has to press play, after which the model asks the user some questions. Then the model runs automatically either for one camp or all camps. Every module has a clear structure: constants, input, calculations and output. The model uses three input CSV files and produces one output CSV file where output on all camps is stored. In addition, the Python code allows following the calculations as they are written down in the Python Editor.

The main advantage of the Python model is the time it takes to run the model for all camps. For any scenario, it takes only a few clicks to achieve this: running the demand module, the technical module and the financial module, together with typing "all" in the Python console for every module. The total computational time to do this is a few minutes. As there is only one place where input is required from the user, the model is less prone to human mistakes, such as forgetting to adjust certain parameters.

In terms of modularity, all constant numerical values could be adjusted when more data is collected in the future and the model would still work properly. This includes changing the demand projection time frame of 5 years and the annual demand growth of 10 years in the demand module, but also the simulation period of 20 years in the financial module, the replacement time of assets, prices of assets and many other constants in each module.

3.4. Comparison of results

Comparing the results of KALO 1.0 and KALO 2.0 had some complications. As there were small adjustments made in KALO 2.0, the results are not the same as the ones reported in the database of Baldi (2021). Therefore, the adjustments were made to KALO 1.0 as well, to be able to make a comparison. However, as KALO 1.0 has to be run manually for each camp, adjusting several parameters, it was not sensible to generate new results for all camps. Therefore, a few camps were chosen to compare the two models. In addition, only a few indicators are discussed here (the LCOE-all), using certain assumptions (Baseline 80%, Tier 2 100% and Tier 3 80% scenarios), although all output indicators and the other scenarios were also compared.

The chosen camps are the following: Moyo is a camp with only the population number known, where a substation is included for both ECR_{hh} scenarios; Ali Addeh has an existing mini-grid; Hol-Hol has data on the number of households, businesses and institutions and does only include a substation for the ECR_{hh} 100% scenario and Abu Matarig is a small camp where no substation will be necessary. These camps give a short but complete representation of the cases encountered. Only the LCOE-all is shown because this indicator depends on all output indicators. When this value corresponds, the others do too. The results are shown in Table 7. It can be seen that there is only a small deviation in values. This is because Python reads the CSV files with a maximum of 9 decimals, while the average family size and the peak sun hour values have more than nine decimals in KALO 1.0.

Table 7. Results on the LCOE-All for four camps and three scenarios.

Camp	Scenario	KALO 1.0 LCOE-all	KALO 2.0 LCOE-all
Moyo	Baseline 80%	62.550	62.554
	Tier 2 100%	48.501	48.505
	Tier 3 80%	37.452	37.456
Ali Addeh	Baseline 80%	63.236	63.240
	Tier 2 100%	48.816	48.819
	Tier 3 80%	37.335	37.338
Hol-Hol	Baseline 80%	59.452	59.456

	Tier 2 100%	48.512	48.516
	Tier 3 80%	30.341	30.344
Abu Matarig	Baseline 80%	53.961	53.965
	Tier 2 100%	39.816	39.819
	Tier 3 80%	28.709	28.711

With this table, the first part of this research is concluded and the first objective is met. The KALO Excel model was successfully reproduced in Python, where a demand module, a technical module and a financial module were built. Small improvements in terms of structure, content and user-friendliness were implemented and the results of the Python model matched with the results of the KALO Excel model. Now the research moves on to the second objective, which is about the larger model improvements.

4. Results Part II: KALO 2.1 - Larger model improvements

This chapter gives the results of the larger model improvements that are implemented. Three of the larger model improvements identified in Section 3.1 are implemented in the Python model, creating the KALO-model 2.1. The first improvement is the option to use a diesel generator in hybrid form with the PV-battery mini-grid, where the diesel generator covers the peak demand. The second improvement is comparing another technological option for electricity access in refugee camps, which is grid extension, with a mini-grid. The third and last improvement is the inclusion of the electricity demand for clean water production, including water pumping and purification. These three improvements were chosen, because sufficient literature was found on these topics during desk research. The other areas of improvement identified earlier in Section 3.1 required more data collection, which would have been difficult due to data scarcity in the field of refugee settlements. The three improvements match with the focus of this study, which is on modelling rather than on data collection.

4.1. Diesel

This section describes the addition of a diesel generator in the Python model. It starts with giving motivation for the strategy used by presenting a small literature review. The section continues with a general description of the diesel part of the model, followed by a description of the adjustments made in each module. Lastly, the results of these improvements are presented and compared with existing literature.

In refugee settlements, electricity is mainly provided by off-grid diesel generators (Neves et al., 2021) (Alonso et al., 2021). Hybrid renewable energy systems (HRES) can reduce the dependency of a camp on diesel fuel, which is often imported over large distances and sensitive to sudden rises in the diesel price (IRENA, 2016) (Neves et al., 2021). In addition, HRES can overcome the fluctuating nature of renewable electricity generation and reduce the generation cost compared to diesel generators (Zebra et al., 2021) (IRENA, 2016) (Neves et al., 2021). However, hybrid or fully sustainable systems have higher upfront costs than diesel systems. The goal of the diesel improvement is to see the financial (dis)advantages of a hybrid mini-grid with diesel compared to a fully renewable mini-grid and to compare different levels of hybridization.

It is important to point out again that the KALO-model is a sizing model, not a simulation model. There is a fixed daily energy demand and load profile for every day of the year, which makes it possible to scale the PV and battery size to meet this demand in a straightforward manner (there is no randomness in the demand). Therefore it was chosen to model a diesel generator, starting from a user-defined percentage of the demand covered by the diesel generator (more details below). Hence, including a diesel generator results in a lower load profile for the PV-battery system.

Diesel generators can be modelled using a load following or a cycle charging strategy. According to the literature (Micangeli et al., 2020), the <u>load following strategy</u> entails that renewable energy sources are used first, followed batteries. Diesel generators are used as a final option. The generator is used to cover the demand that is not met by the solar-battery system. Note that, in this case, the diesel generator does not charge the batteries. The <u>cycle charging strategy</u> follows the same merit-order criterion as the load following strategy, only the diesel generator is used to meet demand and to charge the battery. This latter strategy is used in this research. As better explained below, a constraint is added, so that the diesel generator must operate at a given minimum power when it is turned on. When the diesel output at any point in time is larger than the demand that has to be met, the electricity is used also to charge the battery.

The open-source CLOVER model, used by Alonso et al. (2021), is used as the main guidance to build this new part of the model. It uses the same programming language, which makes it easier to understand its approach, and the scripts behind the model are publicly available (Sandwell, n.d.). The KALO-model from Baldi (2021) also contained some information about diesel, but it was never used in his research. Therefore the diesel part of KALO 1.0 was not fully developed.

4.1.1. General description

The goal of the technical module, including a diesel generator, is to calculate the diesel generator size and the reduced PV and battery capacity. Figure 4 gives a qualitative description of the flow of the model, which will be explained here.

1. The daily load profile of the demand, $LP_{tot}(t)$, in year 6 is used as input data. This is a 1x24 vector that gives the demand for every hour of the day.
2. The user defines a diesel peak percentage. This percentage defines which fraction of the daily peak demand will be covered by the diesel generator and can have any value between 0 and 100%. Examples of three diesel peak percentages are indicated as "threshold" in Figure 5. When the peak percentage is 30%, the generator will switch on when the demand is at 70% of its daily peak value, which is at 102 kWh for the Moyo refugee camp.
3. Two new load profiles are generated. $LP_{SB}(t)$ gives the demand for the solar-battery system and $LP_D(t)$ for the diesel system, for every hour of the day. Both are 1x24 vectors.
4. The strategy used in this research is the cycle charging strategy, which was explained earlier in Section 4.1. This implies that the generator operates at a given minimum power when it is turned on. In this research, the generator has to run at at least 35% of its maximum capacity (Alonso et al., 2021). This is defined as the minimum generator load factor, $LF_{gen,min}$.
   Hence, a loop starts that goes over every hour of one day. Starting from $LP_D(t)$, which defines for which hours of the day the generator is turned on, the first step is to calculate the generator load factor, $LF_{gen}(t)$, during these hours. If this load factor is smaller than $LF_{gen,min}$, the generation is increased to 35% of its maximum capacity. This is called the actual generation from diesel, $LP_{D,N}(t)$.
5. The difference between the actual generation from diesel, $LP_{D,N}(t)$, and the generation required to meet the demand, $LP_{tot}(t)$, is computed and called the excess diesel energy, $Ex_D(t)$.
6. When $Ex_D(t)$ is smaller than zero, the solar-battery system covers the demand (now equal to $-Ex_D(t)$). During sunlight hours, this demand is covered by the solar PV system, $S_{direct}(t)$, and during dark hours this is covered by the battery system, $DisCH_B(t)$.
7. When $Ex_D(t)$ is larger than zero, this means that there is enough electricity generation from diesel to cover the demand at hour *t* and the excess diesel energy is used to charge the battery $CH_{B,diesel}(t)$.
8. When 24 hours are finished, the sum of the battery discharge over 24 hours, $SUM([DisCH_B(t)])$, is compared to the sum of the battery charging from diesel over 24 hours, $SUM([CH_{B,diesel}(t)])$. When the former is smaller than the latter, there is enough diesel energy to charge the battery fully. When the former is larger than the latter, extra solar energy is required to charge the battery, S_{extra}.
9. The final step is to scale the PV and battery capacity to the total demand for solar PV, $SUM([S_{direct}(t)]) + S_{extra}$, and batteries, $SUM([DisCH_B(t)])$.

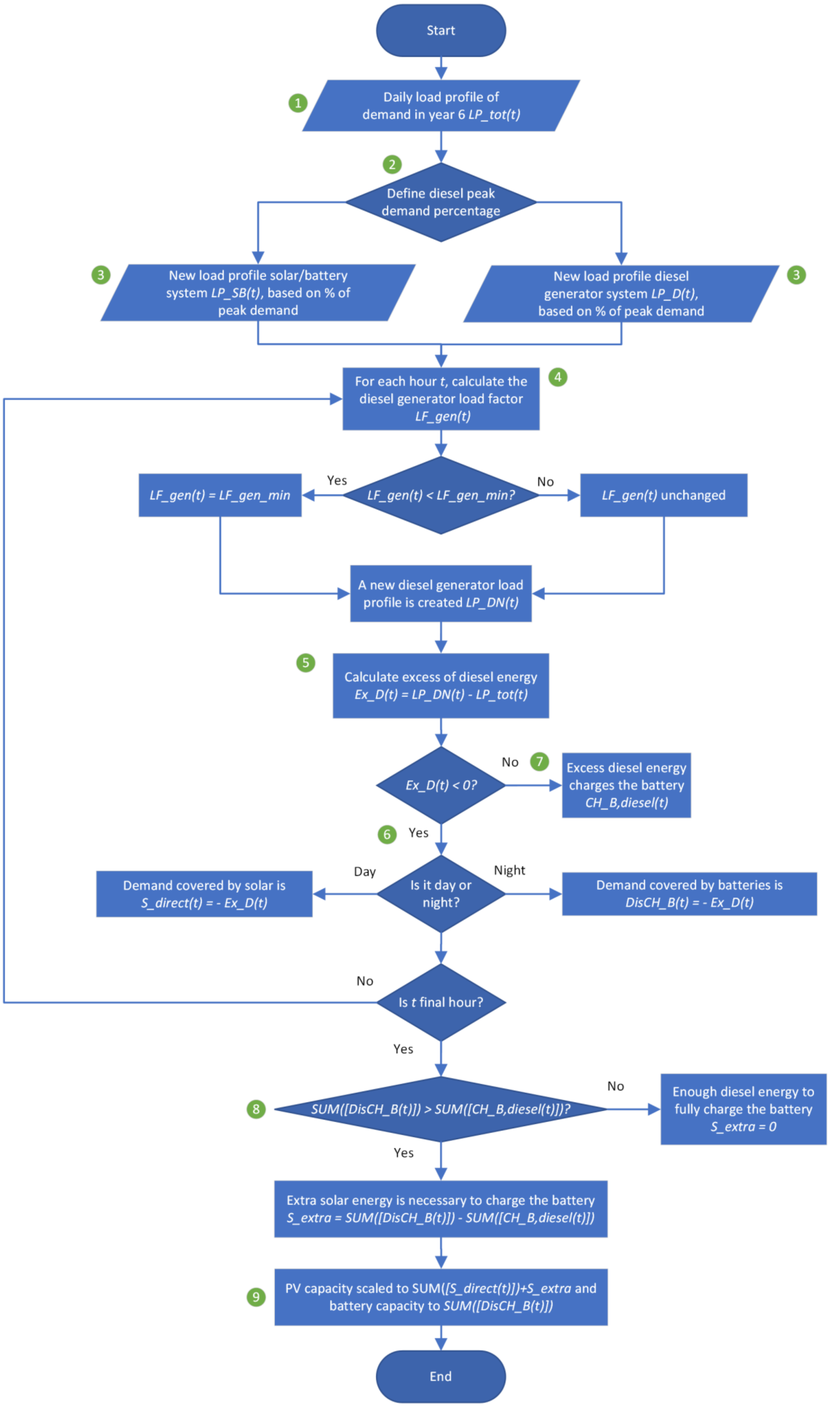

Figure 4. A flowchart describing the diesel part of the Python model.

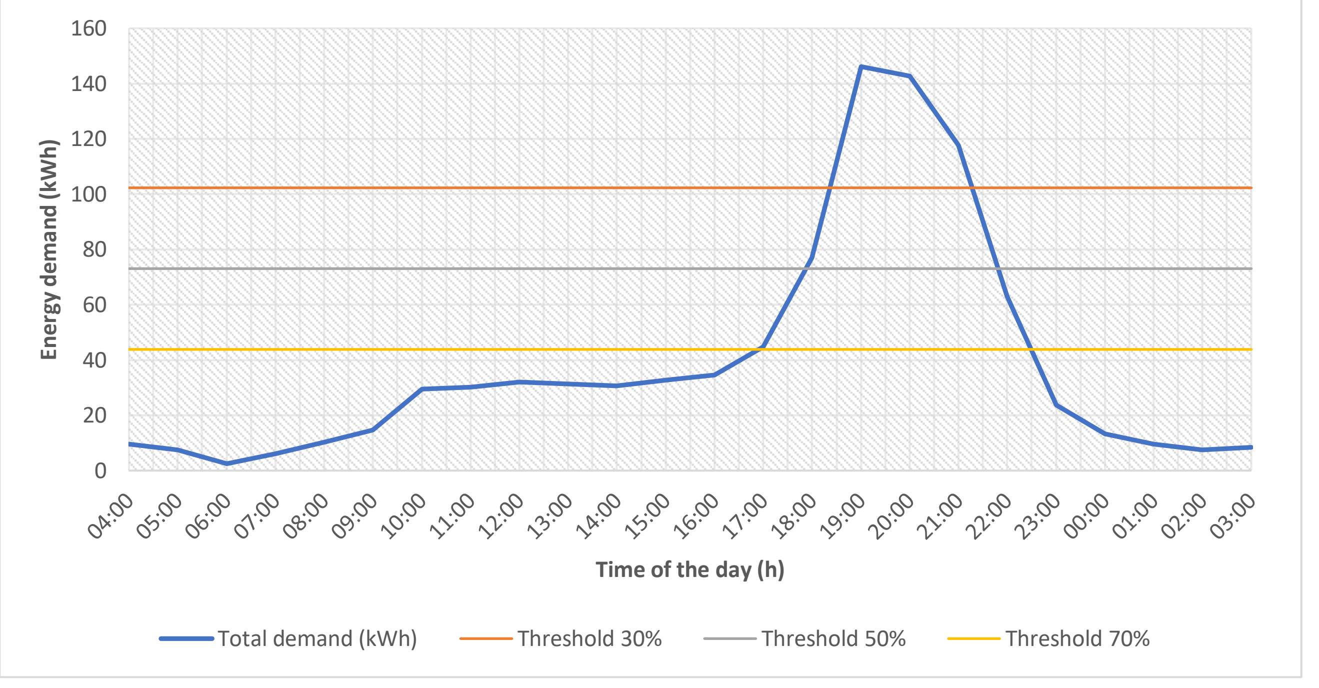

Figure 5. The load profile of the Moyo refugee camp located in Chad, in year 6 for a Tier 2 scenario and an ECR of households of 100%. The horizontal lines show the thresholds for different percentages of the peak demand. The demand above these lines corresponds to the demand covered by the diesel generator.

4.1.2. Adjustments demand module

The diesel peak percentage (= diesel_for_peak in Python) is added to the user input part at the top of the demand module.

The function "peak_shaving" defines the threshold value (see Eq. 21) for which the generator switches on. This function returns the load profiles of the PV-battery system (Eq. 22) and the diesel generator system (Eq. 23) for years 1 and 6. It is the only function regarding diesel included in the demand module.

The *Threshold (kWh)* is computed as:

$$Threshold \;=\; MAX([LP_{tot}(t)]) * (1 - diesel\ peak\ percentage) \qquad \textit{Eq. 21}$$

Where $[LP_{tot,y5}(t)]$ is a vector of 1X24 defining the daily load profile in year 6 (in kWh).

The load profile of the solar-battery system, $LP_{SB}(t)\ (kWh)$, is defined by:

$$LP_{SB}(t) = \begin{cases} LP_{tot}(t), & if\ LP_{tot}(t) < Threshold \\ Threshold, & if\ LP_{tot}(t) \geq Threshold \end{cases} \qquad \textit{Eq. 22}$$

and the load profile of the diesel system, $LP_D(t)\ (kWh)$, is computed by:

$$LP_D(t) = \begin{cases} 0, & if\ LP_{tot}(t) < Threshold \\ LP_{tot}(t) - Threshold, & if\ LP_{tot}(t) \geq Threshold \end{cases} \qquad \textit{Eq. 23}$$

These functions give the demand for the solar-battery and diesel systems at hour *t*. A 1x24 vector can be created when all hours of the day are filled in for *t*. Such a vector is given in square brackets.

The load profiles of both the solar-battery and the diesel system in both years 1 and 6 are added to the output CSV file, as they are needed in the technical module. The name of the output CSV file is adjusted to "output_file_<scenario_name>_<ECR_hh>_<diesel_for_peak>.csv".

4.1.3. Adjustments technical module

Table 8 gives an overview of the constant numerical values added to the technical module. Their use will be explained throughout this paragraph.

Table 8. Constants that are added to the technical module.

Constant	Value	Unit	Source
Power factor	0.8	- (fraction)	(Niwas et al., 2015)
Diesel minimum load	0.35	- (fraction)	CLOVER model (Alonso et al., 2021)
Battery charging trend	9:00 – 6.1% 10:00 – 10.2% 11:00 – 11.2% 12:00 – 15.6% 13:00 – 16.0% 14:00 – 14.3% 15:00 – 12.2% 16:00 – 8.2% 17:00 – 6.1%	Hour of the day starting at x - %	(Baldi, 2021)

The function "diesel_generator_size" determines the required capacity of the diesel generator, which is equal to the maximum hourly value of the diesel generator load profile, $LP_D(t)$ (Phillip Sandwell, n.d.). The capacity is scaled to the demand in *year 6*, which was also done by Baldi (2021) for solar PV and batteries.

The *generator size (kW)* is computed by:

$$Gen\_size_{excl\ losses} = MAX([LP_D(t)] \qquad \text{Eq. 24}$$

For the financial module, the generator capacity must be a value in kVA. Therefore, a power factor of 0.8 is used to convert kW to kVA (Niwas et al., 2015). No generator efficiency is included in this function, as it is included in the diesel consumption rate of 0.4 l/kWh that is used from the CLOVER model (Alonso et al., 2021). The use of this consumption rate will be discussed later on in Section 4.1.4.

Another function added to the technical module is the "demand_PV_batteries" function, which returns the total demand that needs to be covered by solar PV and batteries in year 6. The function has an hourly timestep and uses a "for" loop to loop over the 24 hours of the day.

This function starts with defining the load factor of the generator (Eq. 25). When this load factor is smaller than the minimum load factor of 35%, the generation increases until the generator reaches a load factor of 35% (Alonso et al., 2021). A new load profile for diesel results from this (Eq. 26). Note that this constraint is only valid when the generator is turned on, which is when the demand for diesel, LP_D, is greater than zero.

The load factor of the diesel generator, $LF_{gen}(t)$ (%), is defined by:

$$LF_{gen}(t) = LP_D(t)/Gen\_size_{excl\ losses} \qquad \text{Eq. 25}$$

and the new load profile of diesel, $LP_{D,N}(t)$ (kWh), considering a minimum generator load factor of 35%, $LF_{gen,min}$, is computed as:

$$LP_{D,N}(t) = \begin{cases} Diesel\_min\_load * Gen\_size_{excl\ losses}, & if\ LF_{gen}(t) < LF_{gen,min}\ and\ if\ LP_D > 0 \\ LP_D(t), & if\ LF_{gen}(t) \geq LF_{gen,min}\ and\ if\ LP_D > 0 \\ 0, & if\ LP_D = 0 \end{cases} \quad \text{Eq. 26}$$

The minimum load factor of 35% is the "leading" constraint. Therefore, the total load profile, $LP_{tot}(t)$, is subtracted from the new load profile of diesel, $LP_{D,N}(t)$. This is defined as the excess diesel energy, $Ex_D(t)$ (kWh), which is computed by:

$$Ex_D(t) = LP_{D,N}(t) - LP_{tot}(t) \quad \text{Eq. 27}$$

Now the demand for the solar-battery system is defined. The same assumptions as described in Table 4, about the fractions of the demand covered by solar PV and batteries during the day, are used here again.

The direct demand for the solar PV system, $S(t)_{direct}$ (kWh), is defined by:

$$S(t)_{direct} = \begin{cases} -Ex_D(t), & if\ Ex_D(t) < 0\ and\ 9{:}00 \leq t \leq 17{:}00 \\ -Ex_D(t) * 0.3, & if\ Ex_D(t) < 0\ and\ t = 7{:}00\ and\ t = 19{:}00 \\ -Ex_D(t) * 0.7, & if\ Ex_D(t) < 0\ and\ t = 8{:}00\ and\ t = 18{:}00 \\ 0, & Otherwise \end{cases} \quad \text{Eq. 28}$$

and the hourly discharge of the batteries, $DisCH_B(t)$ (kWh), is defined by:

$$DisCH_B(t) = \begin{cases} -Ex_D(t), & if\ Ex_D(t) < 0\ and\ 7{:}00 > t > 19{:}00 \\ -Ex_D(t) * 0.7, & if\ Ex_D(t) < 0\ and\ t\ =\ 7{:}00\ and\ t = 19{:}00 \\ -Ex_D(t) * 0.3, & if\ Ex_D(t) < 0\ and\ t = 8{:}00\ and\ t = 18{:}00 \\ 0, & Otherwise \end{cases} \quad \text{Eq. 29}$$

Then the initial charging of the battery is defined. When the electricity generation from diesel, $LP_{D,N}(t)$, is large enough to cover the demand at hour t, $LP_{tot}(t)$, the excess of diesel energy is used to charge the battery. The initial battery charging, $CH_{B,init}$ (kWh), is defined as:

$$CH_{B,diesel} = \begin{cases} Ex_D(t), & if\ Ex_D(t) > 0 \\ 0, & Otherwise \end{cases} \quad \text{Eq. 30}$$

At this point, it is necessary to check whether the battery is sufficiently charged. This is done by subtracting the daily amount of battery charging by diesel, $SUM([CH_{B,diesel}(t)])$, from the daily battery discharge needed to cover the demand, $SUM([DisCH_B(t)])$. When this value is smaller than zero, there is enough battery charging from diesel to cover the daily demand. When this value exceeds zero, additional solar energy is needed to charge the battery. This is defined by S_{extra} (kWh), which is computed as:

$$S_{extra} = \begin{cases} 0, & if\ SUM([DisCH_B(t)]) \leq SUM([CH_{B,diesel}(t)]) \\ SUM([DisCH_B(t)]) - SUM([CH_{B,diesel}(t)], & if\ SUM([DisCH_B(t)]) > SUM([CH_{B,diesel}(t)]) \end{cases} \quad \text{Eq. 31}$$

This additional amount of solar energy has to be generated during the sunlight hours. Baldi (2021) assumed that the battery charging from solar energy happens at hour starting at 9:00 to the hour starting at 17:00. He used a battery charging trend for this (see Table 8), which was found during field research in the Kalobeyei refugee camp in Kenya. This trend defines how the battery charges from empty to full during the day. Each percentage defines which fraction of its total capacity the battery charges per hour of the day. The charging trend is stored in a dictionary in Python.

The charging of the battery by solar energy, $CH_{B,solar}(t)$ (kWh), is computed by:

$$CH_{B,solar}(t) = \begin{cases} CH_{trend}(t) * S_{extra}, & if\ 9{:}00 \leq t \leq 17{:}00 \\ 0, & Otherwise \end{cases}$$ *Eq. 32*

Where $CH_{trend}(t)$ is the charging trend from Kalobeyei at hour t.

The demand for solar PV, $S(t)$, has two elements, namely the direct demand for solar energy, $S(t)_{direct}$, and the solar energy needed to charge the battery, $CH_{B,solar}$. This is given by Eq. 33.

$$S(t) = S(t)_{direct} + CH_{B,solar}$$ *Eq. 33*

Figure 6 and Figure 7 give a visual representation of the daily load profile (LP_tot) of the Moyo refugee camp in Chad for a Tier 2 scenario, with an ECR of households of 100%. In the first figure, a diesel peak percentage of 30% is displayed. It can be seen that the generator (LP_dn) is only turned on from the hour starting at 19:00 to the hour starting at 21:00. During the sunlight hours, solar energy is used to both charge the battery (CH_b,s) and cover the demand (S_direct). While during the dark hours, the battery is used to cover the demand (DisCH_b) that is not covered by the diesel generator. The second figure shows a diesel peak percentage of 90%. The diesel generator (LP_dn) is switched on from the hour starting at 09:00 to the hour starting at 23:00. From the hour starting at 09:00 to the hour starting at 16:00 and at 23:00, there is an excess of diesel generation. This results from the minimum generator load factor of 35%, which equals a minimum generation of 46 kWh. This excess is used to charge the battery (CH_b,d) and is enough to charge it fully. Solar energy is only used to cover the demand directly (S_direct) and the battery is used to discharge at night (DisCH_b).

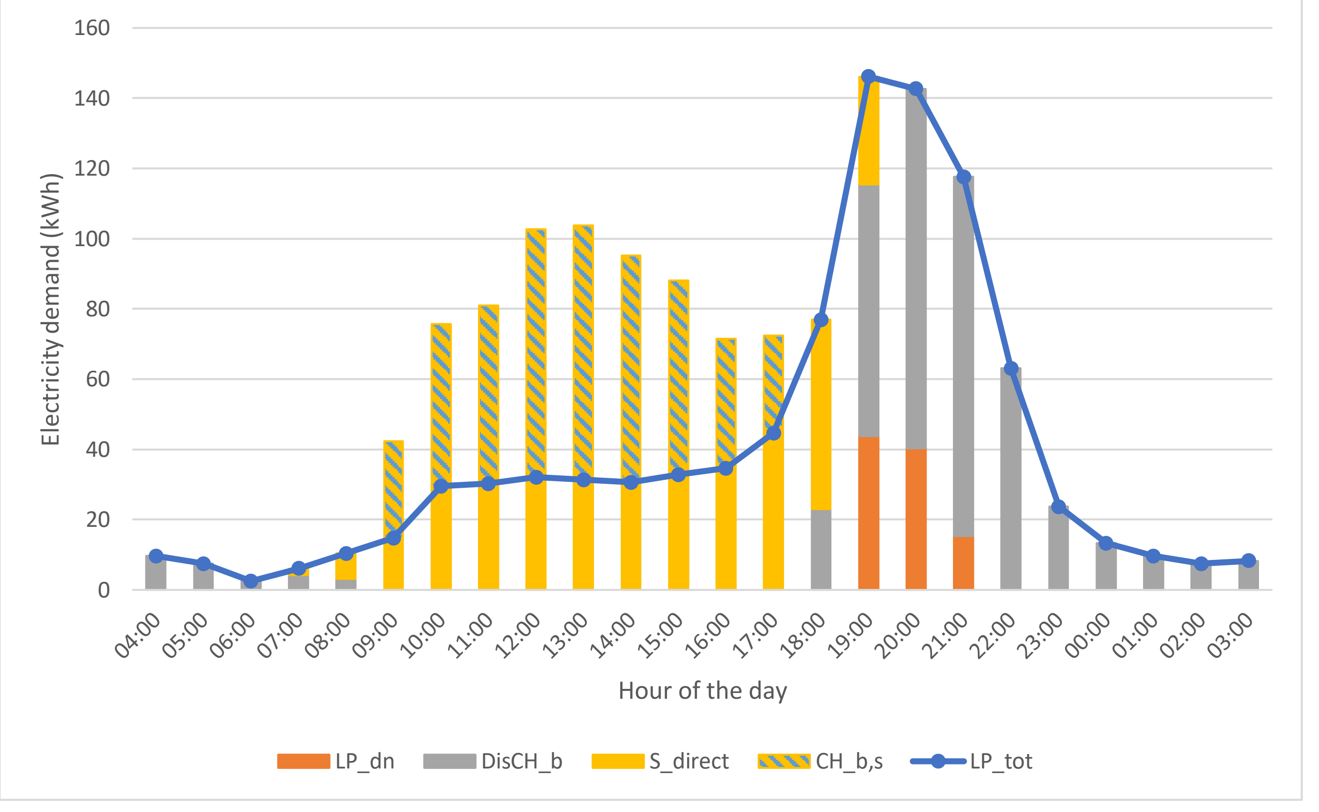

Figure 6. A visual representation of how the daily load profile is covered, with a diesel peak percentage of 30%.

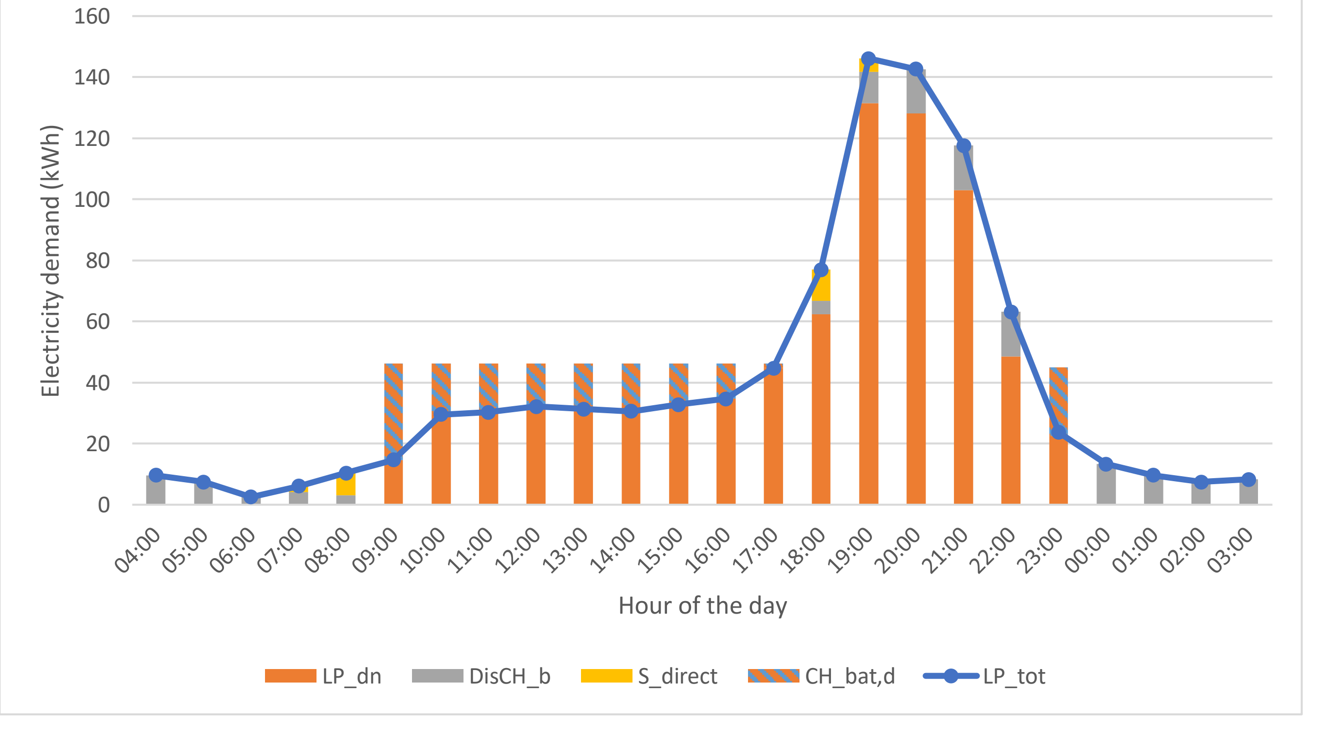

Figure 7. A visual representation of how the daily load profile is covered, with a diesel peak percentage of 90%.

Example calculations using real values for the equations described above are given in Appendix 3, where a diesel peak percentage of 30% and 90% are used. Now that the demand for solar PV and batteries are known, the PV and battery size can be calculated. The same approach as used by Baldi (2021) was taken, also described in Section 3.2.2, where only the demand for solar PV and batteries are changed.

The *PV system size (kWp)* is computed by:

$$PV\ system\ size = \frac{SUM([S(t)]) * (1 + system\ losses) * (1 + reserve\ margin)}{PSH} - kWp\ PV\ existing\ grid \qquad \text{Eq. 34}$$

and the *battery size (kWh)* is defined as:

$$Battery\ size = \frac{SUM([DisCH_B(t)])(1 + system\ losses) * (1 + reserve\ margin)}{Battery\ efficiency} * (1 + (1 - depth\ of\ discharge)) - \ kWh\ Batteries\ existing\ grid \qquad \text{Eq. 35}$$

Finally, the generator size including losses, $Gen_{size_{incl\ losses}}(kW)$, can be calculated by:

$$Gen\_size_{incl\ losses} = MAX([LP_D(t)] * (1 + system\ losses) - Existing\_Gen\_size \qquad \text{Eq. 36}$$

The system losses are included in the calculation of the generator capacity, just as Baldi (2021) did for the PV and battery capacity. In addition, in case there is an existing generator present in the camp (which is at this moment only the case for Kalobeyei Village 1), this amount is subtracted from the required generator capacity, just as was done by Baldi (2021) for the PV and battery capacity. It could be the case that the returned value is negative. When this is the case, the existing generator is big enough to cover the corresponding demand. There is no need to install extra generator capacity. Therefore, the model calculates with zero generator capacity.

The PV and battery capacity are unchanged for a diesel peak demand percentage of 0%, even though the Python code was adjusted. When the diesel peak percentage is 100%, there is no demand for solar PV and batteries anymore and the diesel generator covers all demand.

Another adjustment made in the technical module is the inclusion of the "generation_from_diesel" function. This function calculates the daily electricity generation in year 1 and year 6, which are necessary for calculating the avoided emissions . The same approach was used in the CLOVER model, where they multiplied the load factor with the generator capacity to compute the total amount of electricity generated at hour *t* in kWh (Phillip Sandwell, n.d.).

The electricity generation from diesel (kWh) is computed as:

$$Generation_{diesel}(t) = \begin{cases} Diesel\_min\_load * Gen\_size_{incl\ losses} & if\ LF_{gen}(t) < LF_{gen,min}\ and\ if\ LP_D > 0 \\ LF_{gen}(t) * Gen\_size_{incl\ losses}, & if\ LF_{gen}(t) \geq LF_{gen,min}\ and\ if\ LP_D > 0 \\ 0, & if\ LP_D = 0 \end{cases} \qquad \text{Eq. 37}$$

The avoided emissions in years 1 or 6 (in CO2) are defined by:

$$Avoided_{em(year)} = EF * \frac{\left(eff_{demand_{year}} - SUM([Generation_{diesel}(t)])_{year}\right)}{1000} * Yday \qquad \text{Eq. 38}$$

where *EF* is the emission factor in tCO2/MWh, $eff_{demand_{year}}$ is the effective demand in years 1 or 6, $[Generation_{diesel}(t)]$ is a vector of 1x24 describing the daily profile of electricity generation from diesel and *Yday* are the amount of days in a year.

Eq. 38 was used from Baldi (2021), where the only adjustment was subtracting the daily generation from diesel from the effective demand. Lastly, the output of the module has changed. When running the code for all camps, the Diesel generator size (kVA), Daily generation from diesel in year 1 (kWh) and Daily generation from diesel in year 6 (kWh) are added to the CSV output file. This is done because they are needed in the financial module. Furthermore, the diesel generator size is added as output in the function to run for one camp.

4.1.4. Adjustments financial module

Table 9 gives an overview of the constant numerical values added to the financial module. The use of the first three constants is explained throughout this paragraph, while the use of the last two is explained in Table A. 4.

Table 9. Constants that are added to the financial module.

Constant	Value	Unit	Source
Diesel consumption rate	0.4	Liters per kW capacity per hour	CLOVER model (Alonso et al., 2021)
Price diesel generator	200	USD/kVA	(Baldi, 2021)
Price fuel tank	700	USD	(Baldi, 2021)
Replacement time generator	20	Years	Assumption
Yearly cost reduction generator	0	%	Assumption

The "fuel_cost" function is added to the financial module, which calculates the yearly cost of diesel fuel. The first step to doing this is to calculate the fuel usage. The same calculation as was seen in the CLOVER model is used to do this, which is multiplying the generation from diesel (kWh) with the diesel consumption rate (0.4 l/kWh) (Phillip Sandwell, n.d.). The generation from diesel in year 1 and year 6 are known from the technical module. Linear interpolation is used for the years in between.

Diesel prices per country (USD/l) are used from Baldi et al. (2022) and are added to the "semi_fixed_input.csv" file that Python uses as input. These national prices are corrected for inflation and devaluation over the project's lifetime. More information on that can be found in Appendix 2.3.

The yearly cost of diesel fuel (USD) is defined by:

$$\begin{aligned} Fuel\ cost_{diesel}(year) \\ &= SUM([Generation_{diesel}(t)])_{year} * diesel_{consumption\ rate} * Yday \\ &* diesel\ price \end{aligned} \qquad \text{Eq. 39}$$

Multiple calculations in the financial module of KALO 2.0 include a multiplication with the $PV\ system\ size$. These calculations are:

- Substation upfront costs
- Other upfront costs: logistics & project management cost
- Other upfront costs: contingency cost
- Connections belonging to an existing mini-grid

The $PV\ system\ size$ is replaced by ($PV\ system\ size + Gen\_size_{incl\ losses}$) in the four cases mentioned above. These calculations would be zero for a system running fully on diesel, while they are still valid.

The generator upfront cost and yearly fuel cost are used in the LCOE calculation. The final adjustment to the financial module is to add diesel electricity generation in year 6 to the electricity generation function used for the LCOE.

The yearly electricity generation (kWh) is defined as:

$$Generation_{electr} = \left(PV_{size} * PSH + SUM([Generation_{diesel}(t)])_{year6}\right) * 94.5\% * Yday \qquad \text{Eq. 40}$$

where 94.5% are the generation hours per day (Baldi, 2021). This value corrects for system failures or other issues, reducing the electricity generation over the year. As Baldi (2021) used the PV capacity in this function (which is scaled to the demand in year 6), the electricity generation from diesel in *year 6* is used in this calculation.

4.1.5. Results of diesel adjustments

The financial results of adding a diesel generator to the system are given in Figure 8. This figure shows the diesel peak percentages from 0% to 100% on the x-axis, with a step of 10%. On the y-axis, the corresponding values for the LCOE-all are displayed. The three colors of bars that are displayed are results for three different camps. The trend seen in most camps is displayed by the Moyo refugee camp in Chad, with a diesel price of 0.85 USD/liter. There is a slight increase in the LCOE when the diesel peak percentage increases, until a certain point that is 80% for this scenario. For a diesel peak percentage of 80 and 90%, the LCOE is much higher than for lower diesel peak percentages. This can be explained by the fact that there is unused energy in the system for these percentages.

The daily amount of unused energy (kWh) is defined as:

$$Unused\ energy = \begin{cases} 0, & if\ SUM([DisCH_B(t)]) \geq SUM([CH_{B,diesel}(t)]) \\ SUM([CH_{B,diesel}(t)] - SUM([DisCH_B(t)]), & if\ SUM([DisCH_B(t)]) < SUM([CH_{B,diesel}(t)]) \end{cases} \qquad \text{Eq. 41}$$

From Figure 7 in Section 4.1.3, it can be derived that for a diesel peak percentage of 90%, the diesel generator is switched on already at 9:00, creating an excess of diesel energy from hours starting at 9:00-16:00 and at 23:00. The daily battery charging from diesel is higher than the daily battery discharging. The unused energy, in this case, is 33.6 kWh per day in year 6 and onwards, over a lifetime of 20 years. It is electricity production that is paid for but which is unused. In addition, the upfront cost of solar PV and batteries still exists when the diesel peak percentage is 80% or 90%. For a diesel peak percentage of 100%, there are no upfront costs for solar PV and batteries anymore.

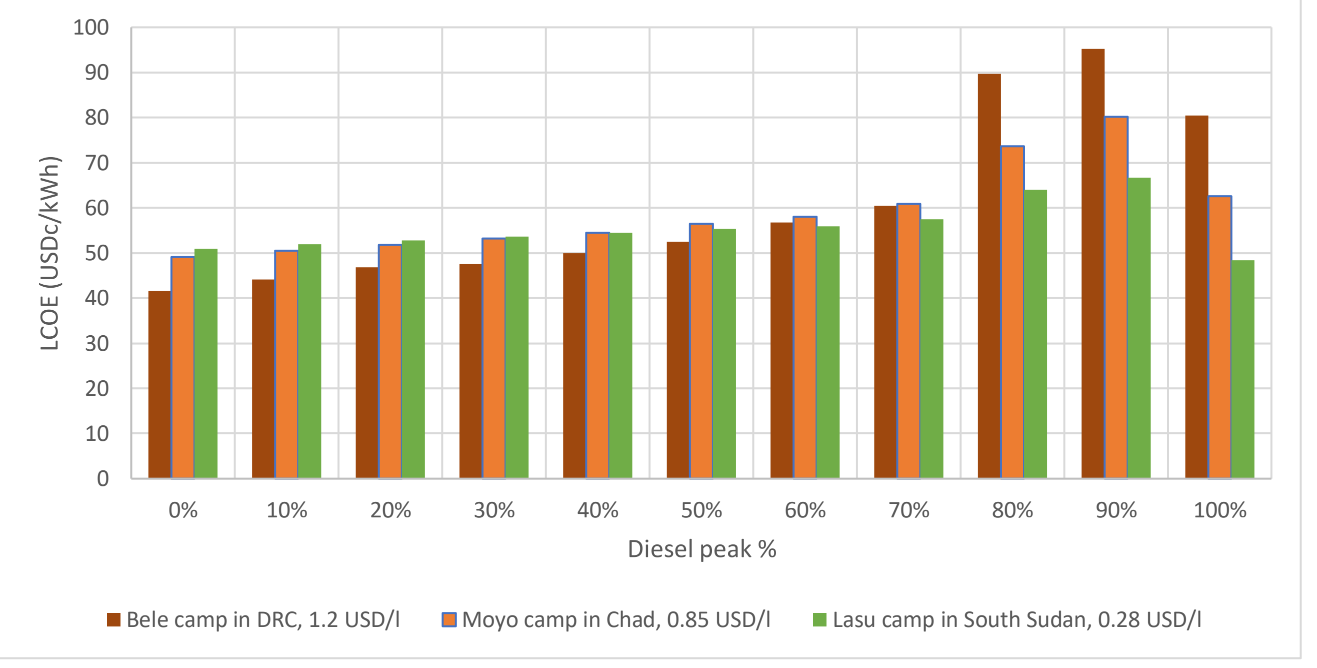

Figure 8. Results of the KALO 2.1 model, for different diesel peak percentages, for different selected camps. Results are given for the Tier 2 scenario and an ECR_{hh} of 100%.

When the diesel price is high, such as in DRC (1.2 USD/liter), a steeper increase in LCOE is seen for diesel peak percentages until 70%. The increasing fuel costs are higher than the decreasing upfront costs for solar PV and batteries. The same peaks in the LCOE as for the Moyo camp are seen at diesel peak percentages of 80% and 90%, which can be explained by the same reason. However, the price of diesel is higher, resulting in more expensive unused energy and a higher LCOE. Countries with a low diesel price, such as South Sudan (0.28 USD/liter), show a flatter increase in LCOE for diesel peak percentages until 70%. Also, the increase in LCOE at diesel peak percentages of 80% and 90% is lower.

There are also differences between camps within one country that have the same diesel price. This is shown in Figure 9, where two camps in Djibouti are presented. The diesel price in Djibouti is 0.98 USD/l. Markazi has a population of 2,150 people and Hol-Hol of 6,359. It can be derived from this figure that the lower the population, the lower the LCOE for all diesel peak percentages. This is because the upfront costs of building the mini-grid are lower for smaller camps, as less PV and battery capacity need to be installed.

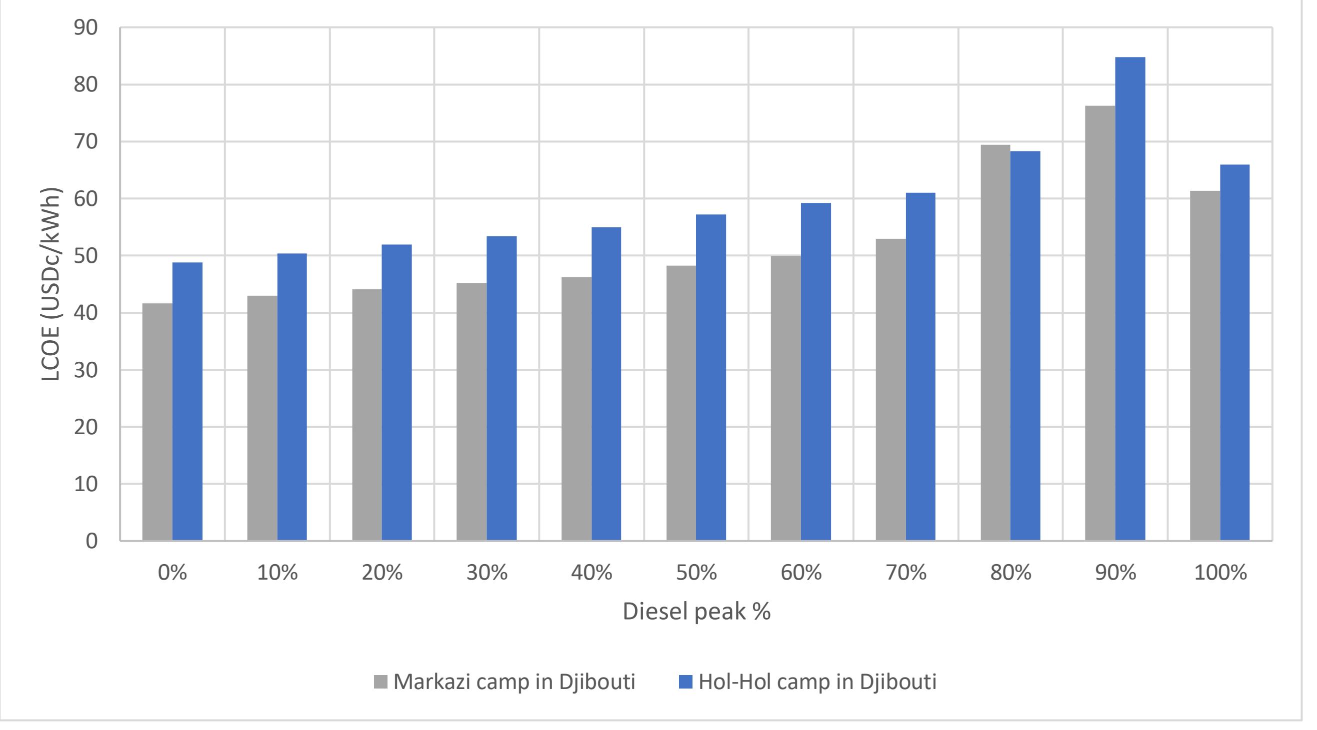

Figure 9. Results of the KALO 2.1 model, for different diesel peak percentages, for the three camps in Djibouti. Results are given for the Tier 2 scenario and an ECR_{hh} of 100%.

The results presented in this section focus on one scenario, which is the Tier 2 demand scenario with an ECR_{hh} of 100%. This is because the trend stays the same for the other demand scenarios, only the height of the LCOE changes. For higher demand scenarios, the LCOE becomes lower.

4.1.6. Comparison with the literature

The results presented in the previous section are now compared to the existing literature. Table 10 gives an overview of the comparison.

Table 10. Mini-grid cost found in literature for fully diesel, solar-diesel hybrid and fully solar mini-grid systems, compared to the results of KALO 2.1 for a Tier 2 demand scenario and an ECR of households of 100%.

	Indicator	**Fully diesel**	**Hybrid solar-diesel**	**Fully solar**	**Context**
KALO 2.1 Tier 2 - 100%	LCOE-all (USD/kWh)	0.598	0.492	0.456	Average of 288 refugee settlements
KALO 2.1 Tier 2 - 100%	LCOE-GenOnly (USD/kWh)	0.449	0.288	0.264	Average of 288 refugee settlements
Alonso et al. (2021)	LCUE (USD/kWh)	0.557	0.409	0.353	Nyabiheke refugee camp
Neves et al. (2021)	COE (USD/kWh)	0.459	0.279	-	Nyabiheke refugee camp
Comello et al. (2017)	LCOE (USD/kWh)	0.569	0.546	0.380	Rural areas in India
Zebra et al. (2021)	LCOE (USD/kWh)	0.92-1.30	0.54-0.77	0.40-0.61	Rural communities

In this research, the average LCOE-all of a fully renewable mini-grid is 0.456 USD/kWh, while the LCOE-all of a mini-grid running fully on diesel is 0.598 USD/kWh. A hybrid system with a diesel peak percentage of, for example, 30% has an LCOE-all of 0.492 USD/kWh. Also, the LCOE-GenOnly is computed, resulting in LCOE values of 0.449, 0.288 and 0.264 USD/kWh for diesel, hybrid and fully renewable mini-grids, respectively. This trend was also seen by Alonso et al. (2021) and Neves et al. (2021), even though they computed the Levelized Cost of Used Electricity (LCUE) and the Cost of Electricity (COE) instead of the LCOE. Alonso et al. (2021) computed the LCUE for mini-grid configurations in the Nyabiheke refugee camp in Rwanda. They found LCUE values of 0.557, 0.409 and 0.353 USD/kWh for a diesel, a hybrid and a fully renewable mini-grid, respectively. Neves et al. (2021) computed the COE for mini-grid configurations in the Mantapala refugee camp in Zambia. They compared different systems to a reference diesel system with a COE of 0.459 USD/kWh. They found that a hybrid mini-grid with PV, batteries and diesel has a COE of 0.279 USD/kWh.

Other studies focusing on mini-grid configurations in *rural areas* are also used for comparison. The study of Comello et al. (2017) focused on mini-grid configurations in rural India. They report LCOE values of 0.569 USD/kWh for a diesel system, 0.546 USD/kWh for diesel-solar systems and 0.380 USD/kWh for solar-battery systems. Zebra et al. (2021) also report on LCOE values of mini-grid in rural communities, with a range of 0.92-1.30 USD/kWh for diesel systems, 0.54-0.77 USD/kWh for hybrid PV-diesel systems and 0.40-0.61 USD/kWh for fully renewable PV systems.

The trend that is found in this research complies with the trends found in other studies, which is that the electricity costs of a mini-grid decrease when diesel is replaced by solar PV and batteries. Still, the electricity costs of mini-grids found in the literature differ from each other and from KALO 2.1. Input data such as the discount rate, project lifetime and the diesel price influence this, which will be discussed in the sensitivity analysis (Section 0).

4.2. Grid extension

The second larger improvement implemented in the Python model is to compare the technological alternative of grid extension with a mini-grid. The literature identifies grid extension as an option to improve rural electrification, together with mini-grids and decentralized stand-alone systems (Safdar, 2017) (Zebra et al., 2021). Grid extension might work in some cases. However, due to low population densities and dispersed houses, grid extension costs for remote areas are often high (Zebra et al., 2021). In addition, remoteness and difficult terrain are reasons why grid extension is not always the most economical solution (Safdar, 2017). However, in the context of refugee settlements, the population density is higher than in rural areas and there is a high concentration of businesses and institutions (Alonso et al., 2021). Therefore, this improvement aims to compare the upfront and yearly cost of grid extension to these costs for a mini-grid.

To include a grid extension scenario, a new module called 'Grid_extension.py' is created. To run this module, the user only has to press the green play button and answer the questions in the Python console, just as in the other modules. The results are produced automatically. This section starts with a general description of the new module, followed by a presentation of and a discussion on the results.

4.2.1. Description new module

The grid extension module has two goals:

- To compare the Upfront cost of transmission lines for grid extension with the Generation Upfront cost of the solar-battery mini-grid.
- To compare the LCOE-all of a fully sustainable mini-grid with the electricity tariffs for households, businesses and institutions collected by Baldi (2021).

The upfront costs of transmission lines are compared to the *generation* upfront cost of the mini-grid, because it is assumed that the projects' distribution, substation and other upfront costs are the same. A substation, low voltage distribution cables and connections for all consumers within the camp are still necessary. Other upfront costs, including logistics & project management and contingency, are also assumed to be still valid. More information on these costs can be found in Section 3.2.3, Table 6. The LCOE-all of a mini-grid is compared to electricity tariffs because, generally, tariffs include costs of building, financing, maintaining and operating the electricity-generating power plants and the electricity grid, including transmission and distribution lines (EIA, 2022).

The grid extension module has the same structure as the other modules, starting with constants, import of inputs from other modules and import of libraries, followed by calculations for the output. It is important to point out that the demand scenario defined in the demand module is still valid in the grid extension module as it defines which percentage of the households is connected (ECR_{hh}) and the height of the demand (Baseline, Tier 2 or Tier 3). Also, the diesel peak percentage defined at the top of the demand module is still valid in the grid extension module, as a comparison is made with the LCOE-all of the mini-grid.

The camps distances to the grid are used from Baldi (2021) and are added to the "Variables.csv" input file. The capital cost for grid extension of 8000 USD/km is used from Raji & Luta (2019). It is used for illustrative purposes as this study is about grid extension and building a mini-grid for a rural area in South-Africa.

The grid extension upfront cost (in USD) are calculated by:

$$Grid\ extension\ upfront\ cost = 8000\ USD/km * distance\ to\ grid\ (km)$$

The function to run the module for one camp compares the Upfront cost of grid extension with the Generation Upfront cost of the solar-battery mini-grid, by printing both values to the Python console. In addition, the LCOE-all of the solar-battery mini-grid and the national electricity tariffs for households, businesses and institutions (both in USDc/kWh) are printed to the console. The function to run for all camps adds five columns to the output CSV file of the corresponding demand scenario. The first column contains the generation upfront cost of the mini-grid for all camps, the second column contains values of the grid extension upfront cost for all camps and the third, fourth and fifth columns contain the national electricity tariffs for households, businesses and institutions (in USDc/kWh) for all camps. The LCOE-all column for the mini-grid already exists in the CSV file.

4.2.2. Results of grid extension compared to sustainable/hybrid mini-grids

First, the results of the comparison between the generation (GEN) upfront cost of the mini-grid (MG) and the upfront cost of grid extension (GE) are discussed. These are displayed in Figure 10 and Figure 11. The upfront costs of GE are subtracted from the generation upfront cost of the mini-grid. This results in both positive and negative values. Positive values correspond to camps where the upfront costs of grid extension are lower than the generation upfront costs of the mini-grid. In these cases, grid extension would be a more favorable option in terms of upfront cost. When values are negative, a mini-grid would be a more favorable option in terms of upfront cost.

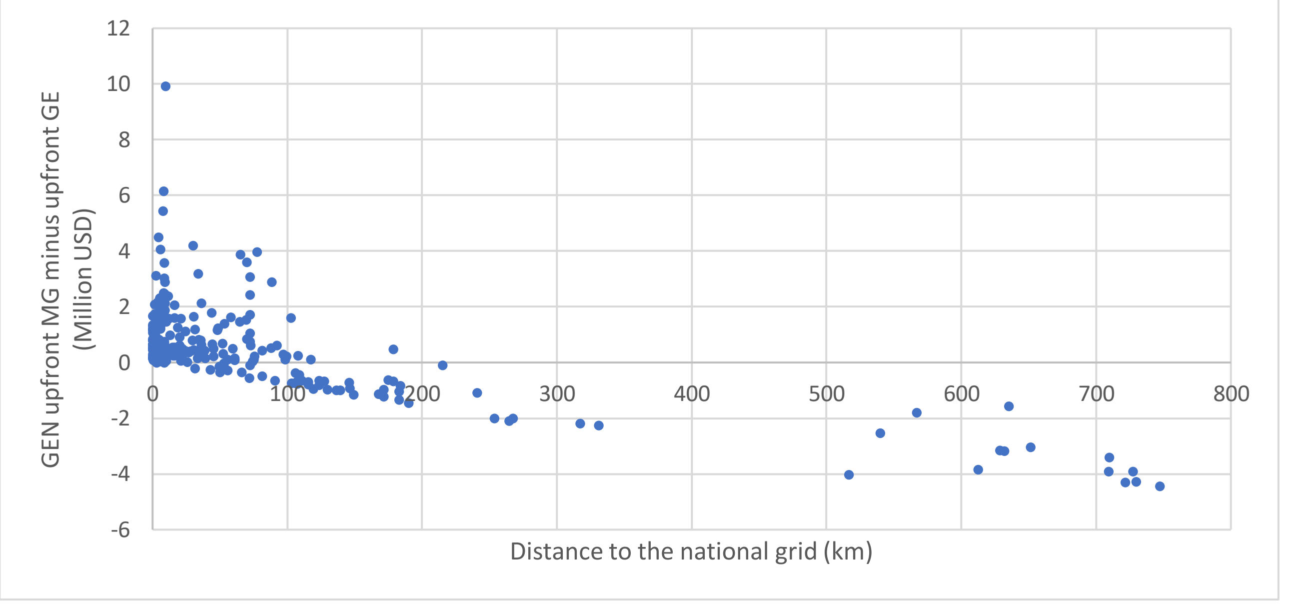

Figure 10. The difference between the Generation (GEN) upfront cost of the mini-grid (MG) and the upfront cost of grid extension (GE) for all camps in the dataset, plotted against the camps distances to the national electricity grid. The results are given for a Tier 2 demand scenario with an ECR_{hh} of 100%. The LCOE-all is computed for a fully renewable system.

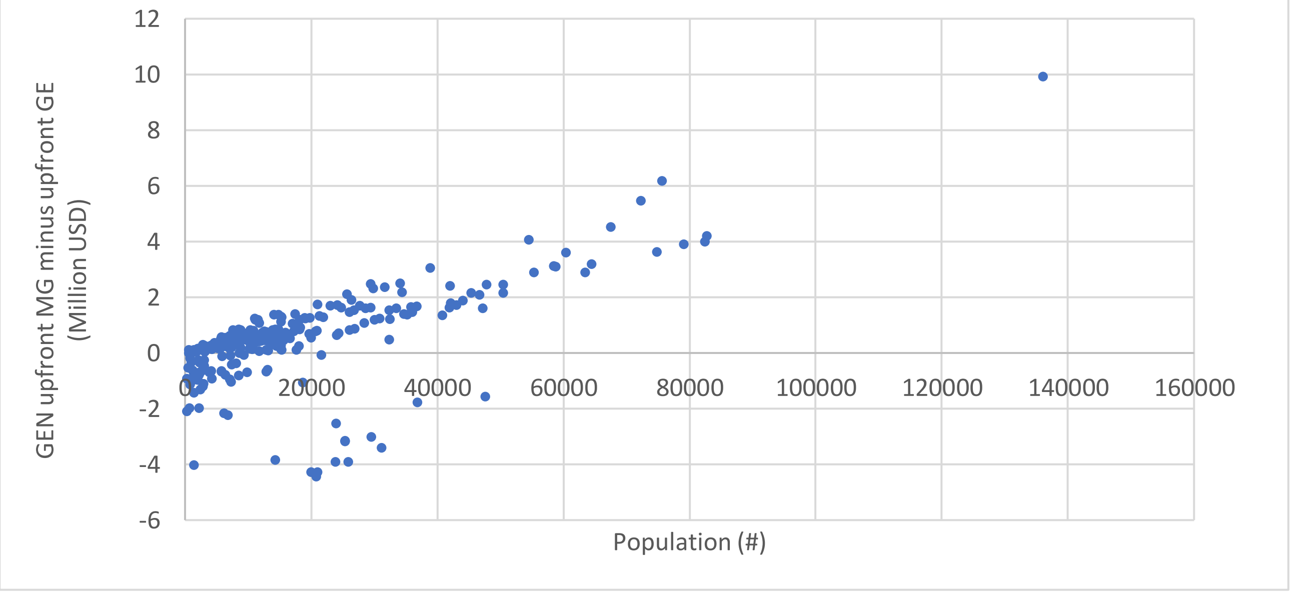

Figure 11. The difference between the Generation (GEN) upfront cost of the mini-grid (MG) and the upfront cost of grid extension (GE) for all camps in the dataset, plotted against the camps population numbers. The results are given for a Tier 2 demand scenario with an ECR_{hh} of 100%. The LCOE-all is computed for a fully renewable system.

From the figures, it can be derived that 78% of the values are positive and 22% are negative. In Figure 10, it is shown that the closer the camp is located to the grid, the lower the upfront costs of grid extension are compared to the generation upfront cost of a mini-grid (resulting in high positive numbers). It can also be derived that for camps located far from the grid, the upfront costs of grid extension are much higher than the generation upfront costs of a mini-grid. This trend is expected as the grid extension upfront costs are calculated in USD/km. All camps, except for one, for which the upfront costs of grid extension are lower than the generation upfront costs of a mini-grid (positive values), are located within 118 km of the grid. The exception is the Kario refugee camp in Sudan, a large camp with over 32,000 inhabitants, located 179 km from the grid.

Some camps have higher grid extension upfront costs than generation upfront costs of a mini-grid (negative values) while they are located close to the grid. An example of such a camp is Adjuman Maaji I in Uganda. This camp is located only 3.1 km from the grid and has a population of 549.

These two observations can be explained by another trend that was found, which is displayed in Figure 11. For large camps, it is generally more attractive to connect to the national grid than to invest in a mini-grid, in terms of upfront cost. This is because the generation upfront costs for a mini-grid in large camps are high, as high capacities of solar PV and batteries are required. For small camps, these generation upfront costs are low. Therefore, a mini-grid is generally more attractive than grid extension, in terms of upfront costs.

For the Nyarugusu refugee camp in Tanzania, the generation upfront costs of grid extension are very high compared to the upfront costs of grid extension (positive value of almost 10 million USD). This camp has a population of almost 130,000 and is the largest camp in the database. Generating electricity with solar PV and batteries has high upfront costs if it has to produce for this large amount of people. The camp is only located 9.6 km from the grid and therefore it is more attractive to connect to the grid than to invest in a mini-grid, in terms of upfront costs. As the camp is only located 9.6 km from the grid, it is more attractive to connect to the grid than to invest in a mini-grid, in terms of upfront costs. The negative values from Figure 11 that still have a relatively large population number (around 20,000 and higher) are camps that are located far from the grid (>500 km).

The second goal of this module is to compare the LCOE-all of the sustainable mini-grid with the national electricity tariffs belonging to a camp. It was found that for all camps in the database, the corresponding electricity tariffs were lower than the LCOE-all. Some examples are given in Table 11. In countries like South Sudan and Chad, where the electricity tariffs are relatively high, the difference between the LCOE-all and the electricity tariffs are the lowest. While in countries where the electricity tariff is low, such in Sudan, the difference is high and the LCOE-all of the mini-grid is much larger than electricity tariffs. For all camps, the costs of electricity are lower for grid extension than for a sustainable mini-grid.

Table 11. A comparison between the LCOE-all of a sustainable mini-grid with the national electricity tariffs of households (hh), businesses (bus) and institutions (inst) for three different camps in three different countries.

	LCOE-all (USDc/kWh)	**Tariff hh (USDc/kWh)**	**Tariff bus and inst (USDc/kWh)**
Gorom camp in South Sudan	43.72	41.99	41.99
Vom camp in Chad	42.33	32.42	32.42
Abuda camp in Sudan	39.99	0.2712	0.3255

In the research of Raji & Luta (2019), the total Net Present Costs (NPC) of a community mini-grid are lower than those of grid extension for distances larger than 130.84 km from the national grid. They used the HOMER software to calculate this, with O&M costs of 160 USD/year/km and a grid energy price of 0.1 USD/kWh. The study from Moretti et al. (2019) mentions that the electricity prices from the national grid are lower than installing and operating a mini-grid system. However, there are upfront costs involved relating to new transmission lines that have to be constructed. Both these findings are in line with the result of the grid extension module of this research.

4.3. Clean water production

Besides energy, clean water is acknowledged as one of the most essential needs in emergency situations. In these situations, clean water is essential for survival, but also for hygienic practices and cooking. Disasters (natural or man-made) may lead to the destruction of water pipelines and water pumps, and saltwater intrusion may occur in shallow wells. When clean and portable water becomes scarce, it can increase the risk of waterborne diseases. In humanitarian relief settings, clean water is often supplied in water bottles, even in protracted/chronic situations. This results in high costs and security issues (Fuso Nerini et al., 2015). Loo et al. (2012) mention that it is more practical to install onsite water technology than to deliver water to the camp in the form of water bottles or water tanks. Still, water treatment within the camp can be challenging due to bad and changing water quality and limited access to resources and infrastructure. Limited access to the national electricity grid can prevent using energy-dependent technologies (Loo et al., 2012). However, the presence of a mini-grid in refugee settlements could allow for electricity-based clean water production.

Neves et al. (2021) assume that the water supply in a refugee camp would be 20 liters/person/day. Implementing clean water production requires installations for water pumping and water purification (Neves et al., 2021). A typical installation for water pumping has a capacity of 37 kW, running for 7 hours a day during sun peak hours (from 9:00 to 16:00), resulting in a production of 240,000 l of water per day (Neves et al., 2021). This corresponds to a water pumping capacity of 1.08 Wh/l. A typical installation for water purification has a capacity of 2.5 kW. It could be run for either 13 or 24 hours a day, resulting in either 5000 or 9231 l of purified water per day (Neves et al., 2021). This corresponds to a water purification capacity of 5.85 Wh/l. An overview of the constant numerical values added to the demand module can be found in Table 12. Neves et al. (2021) point out that water purification can also be done with chlorination, which would not require electricity.

Table 12. Constants added to the demand module for the inclusion of clean water production.

Constant	Value	Unit
Water usage per person per day	20	l/person/day
Water pumping size	37	kW
Water pumping production	240000	l/day
Hour of start water pumping	9:00	-
Hour of end water pumping	16:00	-
Water purification size	2.25	kW
Water purification 13 hours	5000	l/day
Water purification 24 hours	9231	l/day
Hour of start water purification	0:00 or 8:00	-
Hour of end water purification	24:00 or 21:00	-

A new function is added to the demand module, called "load_profile_clean_water_prod", containing the equations described below. The function returns the daily load profile of water pumping and water purification.

The total amount of liters that is needed in a camp per day is calculated by:

$$liters\ per\ day = population * water\ usage\ per\ person\ per\ day \qquad \text{Eq. 42}$$

The daily energy demand of water pumping (kWh/day) is computed by:

$$Daily\ energy\ demand\ pumping = water\ pumping\ size (kW) * \frac{(hour\ of\ end - hour\ of\ start\ pump)}{water\ pumping\ production\ (\frac{l}{day})} * liters\ per\ day \qquad \text{Eq. 43}$$

and the daily energy demand of water purification (kWh/day) is defined as:

$$Daily\ energy\ demand\ purification = water\ pur.size(kW) * \frac{(hour\ of\ end - hour\ of\ start\ pur.)}{water\ pur.13\ or\ 24\ hours\ (\frac{l}{day})} * liters\ per\ day \quad \text{Eq. 44}$$

The daily energy demand for water pumping and purification will be divided by the hours of the day that the installations run. The shorter the running period of the installation, the higher the hourly demand. The daily load profile of water pumping, $LP_{W,pump}(t)\ (kWh)$, is computed as:

$$LP_{W,pump}(t) = \begin{cases} \frac{Daily\ energy\ demand\ pumping}{hour\ of\ end - hour\ of\ start\ pumping}, & if\ hour\ start \leq t < hour\ end\ pumping \\ 0, & Otherwise \end{cases} \quad \text{Eq. 45}$$

and the daily load profile of water purification, $LP_{W,pur}(t)\ (in\ kWh)$, is defined as:

$$LP_{W,pur}(t) = \begin{cases} \frac{Daily\ energy\ demand\ purification}{hour\ of\ end - hour\ of\ start\ purification}, & if\ hour\ start \leq t < hour\ end\ pur \\ 0, & Otherwise \end{cases} \quad \text{Eq. 46}$$

These load profiles are added to the daily load profile computed for the demand, defined in Section 3.2.1. The resulting daily load profile is given in Figure 12, where the Moyo refugee camp in Chad is used as an example.

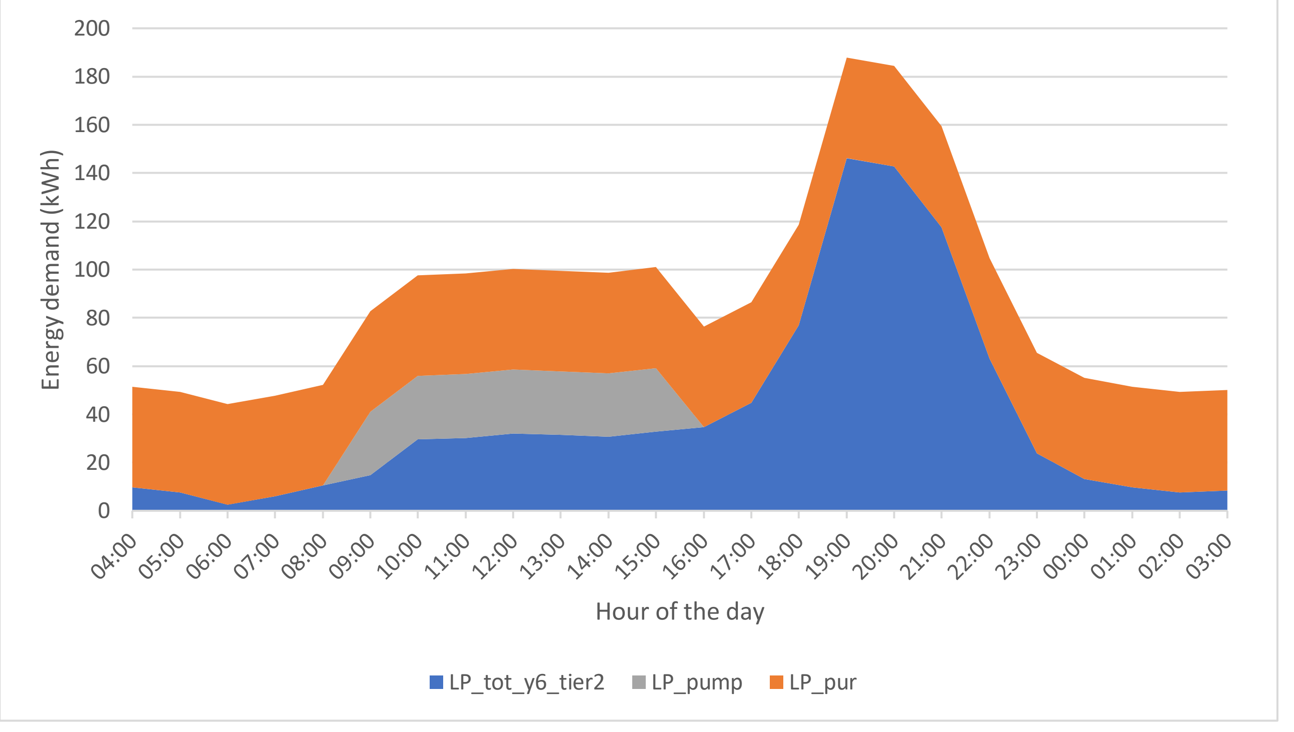

Figure 12. The daily load profile of the demand and clean water production. The results are given for the Moyo refugee camp in Chad, for a Tier 2 demand scenario and an ECR_{hh} of 100%.

The load profile of the demand in year 6 (LP_tot_y6) is plotted in blue, the load profile of water pumping (LP_pump) in grey and the load profile of water purification (LP_pur) in orange, using a stacked area diagram. It can be derived that the water purification is constant over 24 hours and that the water pumping is performed during peak sun hours. The daily energy demand is increases by 20% if only water pumping is considered. When both water pumping and purification are considered, the daily energy demand increase by 128%. It is important to point out that these percentages are true for the Tier 2 demand scenario with an ECR_{hh} of 100%. Increasing the demand scenario from Tier 2 to Tier 3 results in an increased energy demand of just 4% for water pumping and 29% for both water pumping and purification. This is shown in Figure 13. The increase in energy demand is lower because the amount of liters needed in the camp stays constant (as it only depends on the population).

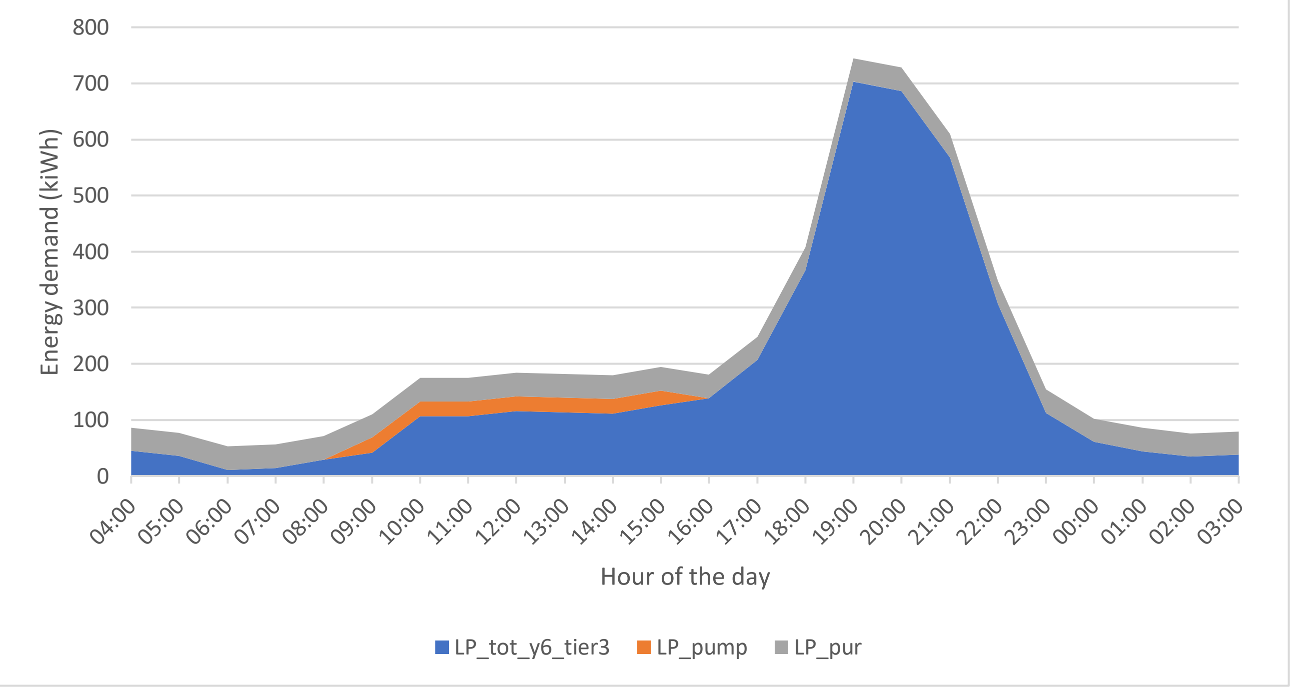

Figure 13. The daily load profile of the demand and of clean water production. The results are given for Moyo refugee camp in Chad, for a Tier 3 demand scenario and an ECR_{hh} of 100%.

Lastly, the effect of clean water production on the LCOE is assessed. The results are given in Table 13 for a Tier 2 and Tier 3 demand scenario. Three LCOE values are given for the Moyo refugee camp in Chad: the LCOE-all excluding clean water production, the LCOE-all including water pumping and the LCOE-all including both water pumping and purification. It can be seen that including both water pumping and purification results in lower values for the LCOE. It can also be derived that in the Tier 3 scenario, the effect of including water pumping and purification on the LCOE is smaller, as the demand excluding clean water production is already higher.

Table 13. The LCOE of the Moyo refugee camp for a fully renewable system, including and excluding clean water production, for a Tier 2 and Tier 3 demand scenario.

	Tier 2	**Tier 3**
LCOE-all excluding clean water production (USDc/kWh)	48.43	37.49
LCOE-all with pump (USDc/kWh)	43.08	36.59
LCOE-all with pump and pur (USDc/kWh)	36.96	35.37

4.4. Sensitivity analysis

The sensitivity analysis aims to assess the effect of changing certain input parameters on the output, in this case, on the LCOE values of the camps. A new module is created in Python called "Sensitivity_analysis.py". To run this module, the user only has to press the green play button and answer the questions in the Python console. This section starts with an overview of the adjusted parameters for the analysis. After that, a description of the Python module is given, followed by the results of the sensitivity analysis.

4.4.1. Adjusted parameters

Five different input parameters are adjusted in the sensitivity analysis, which are summed below. The first three parameters were also changed by Baldi (2021) in KALO 1.0. Argumentation on why these were used can be found in Baldi (2021).

The last two parameters were added to the sensitivity analysis. They were chosen because the literature showed varying values for these two parameters. The range in diesel prices found for countries of the 288 camps in the database is 0.28 - 1.4 USD/l (Baldi, 2021). A diesel price of 2.0 USD/l is considered because the prices found by Baldi (2021) did not consider transportation costs to the camps, which could be remote locations. Therefore, actual diesel prices can turn out to be higher (Baldi, 2021) (Alonso et al., 2021). In addition, diesel prices varying between 0.4 USD/l and 1.6 USD/l were found in the literature (Alonso et al., 2021) (Cerrada & Thomson, 2017) (Moretti et al., 2019) (Neves et al., 2021). Therefore, a broad range in diesel prices of 0.2 USD/l to 2.0 USD/l was chosen. Lastly, a simulation period of 15 years was chosen because this value was used by Alonso et al. (2021).

1. Discount rate:
    - Original value: 10%
    - Original value -20%: 8%
    - Original value +20%: 12%
2. OM cost:
    - Original value: 1% of total upfront cost
    - Original value +100%: 2%
    - Original value +200%: 3%
3. Price customer connection:
    - Original value: 80 USD/connection
    - Original value -25%: 60 USD/connection
    - Original value -50%: 40 USD/connection
    - Original value -75%: 20 USD/connection
    - Original value -100%: 0 USD/connection
4. Diesel price
    - Original value: differs per country
    - Low value: 0.2 USD/l
    - High value 2.0 USD/l
5. Simulation period
    - Original value: 20 years
    - Low value: 15 years

4.4.2. Description Python module

The Python module for sensitivity analysis has the same structure as the other modules, starting with constants and import of inputs, followed by calculations for the output. The ECR_hh, scenario_name and diesel_for_peak are imported from the demand module and the LCOE function is imported from the financial module. New objects are created that define the values of the input parameters (points 1-5 from above). Consequently, these objects are used to calculate new values for the LCOE, using one non-original parameter at a time. This results in 11 new LCOE values per camp, which can be compared to the original LCOE of that camp.

To run for all camps, the CSV output file from the demand, technical and financial module is used as fixed input. The results of the sensitivity analysis are printed to a new CSV file, copying the results from the corresponding financial output file. To run for one camp, the results are printed to the Python console. Note: the sensitivity analysis can be run for any demand scenario defined in the demand module and for any diesel peak percentage. Every type of scenario creates a different CSV file called "output_file_sensitivity_analysis_<scenario_name>_<ECR_hh>_<diesel_for_peak>.csv". For now, the sensitivity analysis is only carried out for the LCOE-all.

4.4.3. Results of the sensitivity analysis

The results for the first three parameters, which are the discount rate, O&M cost and customer connection price, are given in Figure 14. The Moyo refugee camp in Chad is used as an example.

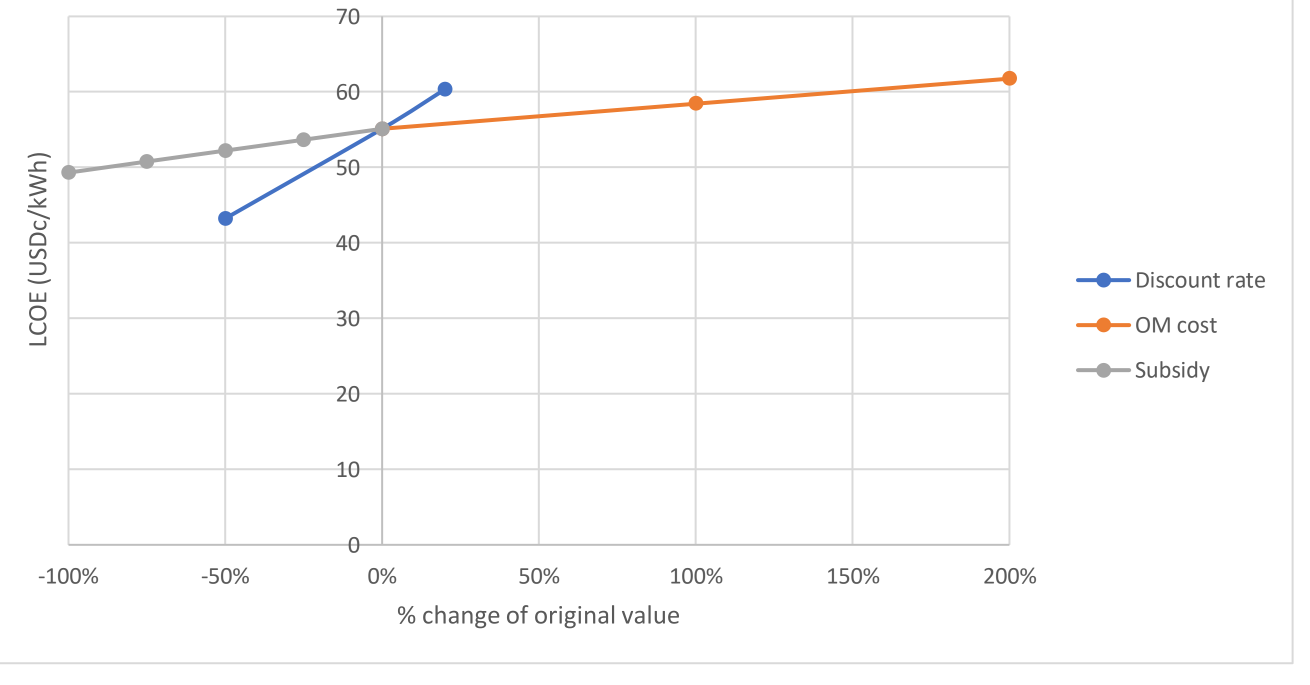

Figure 14. A spider diagram to show the effect of the discount rate, the O&M cost and the subsidy for the customer connection on the LCOE-all, for a Tier 2 demand scenario, an ECR_{hh} of 100% and a diesel peak percentage of 50%.

It can be derived that the discount rate has the highest effect on the LCOE. To make the discount rate fit better with a specific camp's location, the model makes it possible to calculate the LCOE based on national discount rates (LCOE-WACC discussed in Section 3.2.3).

The results of changing the diesel price are given in Figure 15. Again, the Moyo refugee camp is used as an example, for which all parameters are kept constant and only the diesel price is adjusted. The original diesel price used for the Moyo refugee camp is 0.85 USD/l.

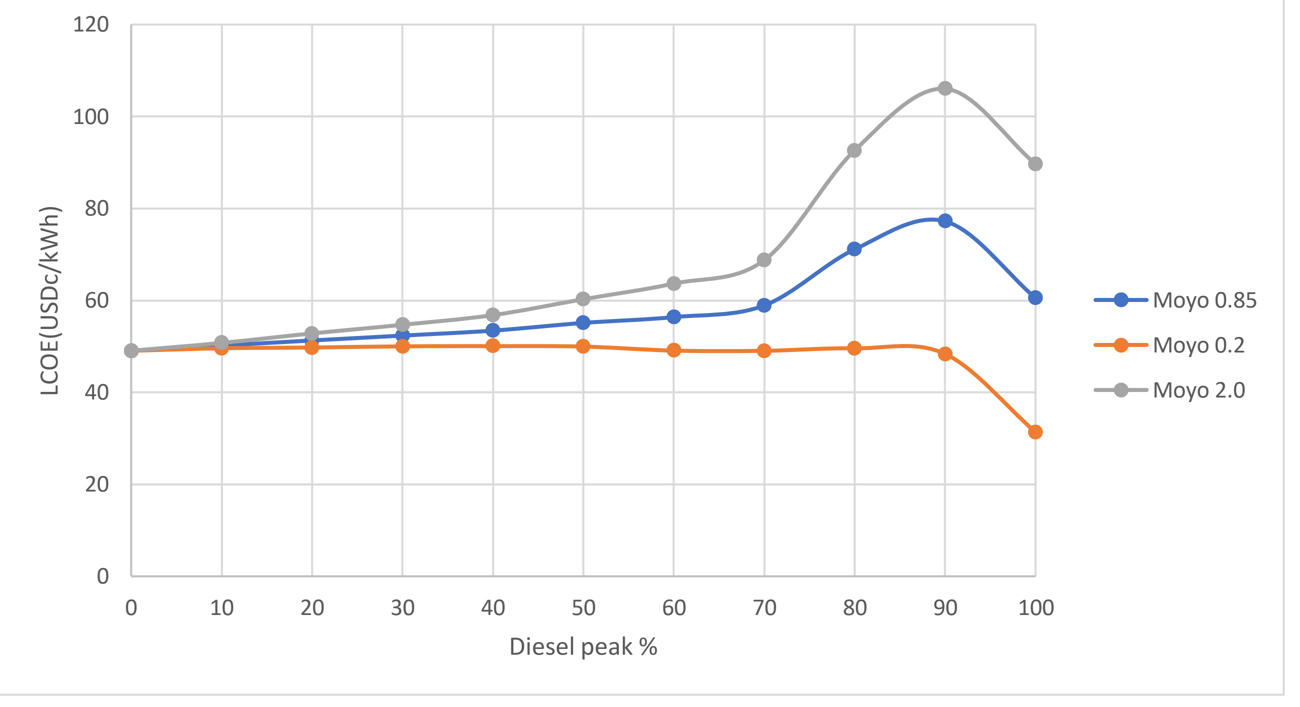

Figure 15. The LCOE-all for different diesel peak percentages and different diesel prices for the Moyo refugee camp in Chad.

It can be derived that a diesel price of 2.0 USD/l results in an increasing LCOE for higher diesel peak percentages, while a diesel price of 0.2 USD/l results in a slightly decreasing LCOE for higher diesel peak percentages. The increase in LCOE around diesel peak percentages of 80% and 90% disappears for a diesel price of 0.2 USD/l.

Lastly, the results of changing the simulation period are given in Figure 16. Initially, the simulation period is set at 20 years (Baldi, 2021). This was adjusted to 15 years to see the effect on the LCOE for different diesel peak percentages.

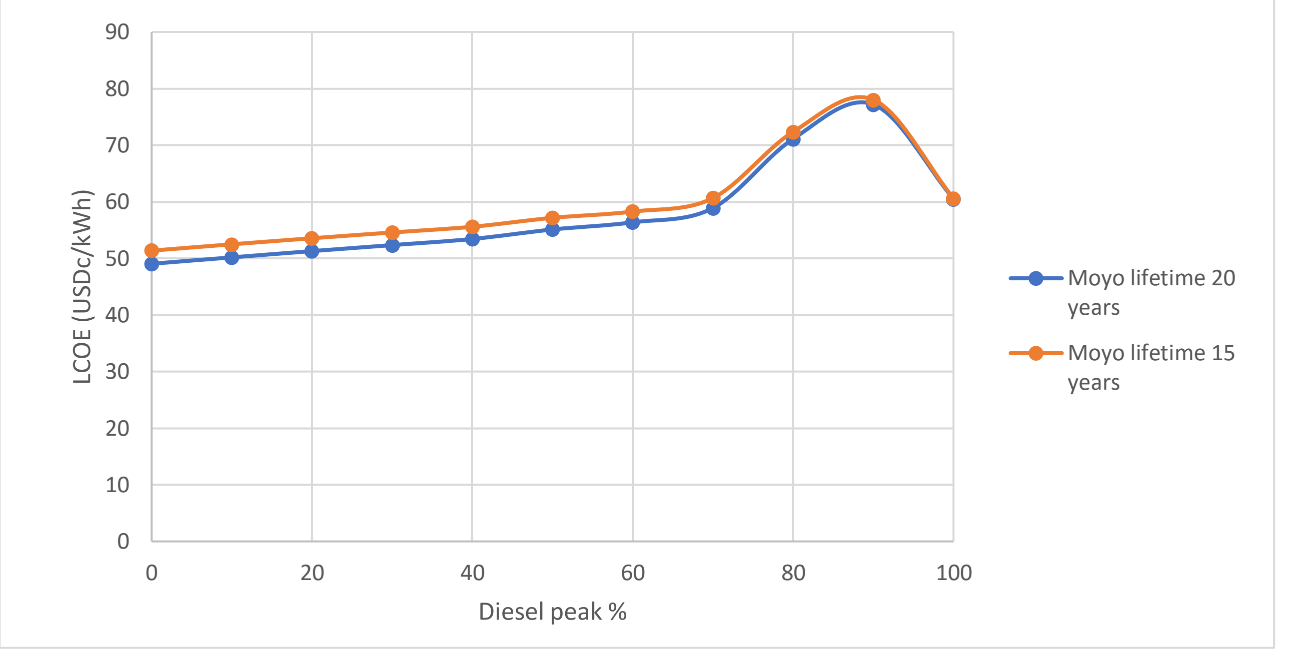

Figure 16. The LCOE-all for different diesel peak percentages and a simulation period of 15 and 20 years for Moyo refugee camp in Chad.

It can be derived that changing the simulation period has only a small effect on the LCOE. For a fully renewable system, the LCOE for the Moyo refugee camp increases by 4.7% when the lifetime is shortened to 15 years, while for a full diesel system, the LCOE stays the same.

With this sensitivity analysis, the second part of this research is concluded and the second objective is met. KALO 2.0 was improved to KALO 2.1. Two additional options for electricity access in the camps were included, namely to use a diesel generator in the system and to connect the camp to the national electricity grid. Lastly, electricity demand for clean water production, including water pumping and purification, was added to the demand module and a sensitivity analysis was carried out. The next chapter will discuss the results that were presented.

5. Discussion

This section gives a discussion on the results that were presented in the previous chapters. It is divided based on the two sub-aims defined in Section 1.4. Section 5.1 discusses KALO 2.0, which is mainly about programming-related limitations. Section 5.2 follows with a discussion on KALO 2.1, where the larger model improvements will be discussed. Section 5.3 gives some more general limitations of KALO 2.1 and the chapter finishes with research-related limitations. Each section gives the limitations together with recommendations for future research.

5.1. KALO 2.0 – Programming-related limitations and future research

Each Python module has to be run individually and the three parameters that define the scenario (corresponding to the scenario_name, ECR_hh and diesel_for_peak) must be defined at the top of the demand module. This is needed because every module creates an output CSV file that depends on these three parameters. This CSV file is needed as fixed input in the next module if the model is run for *all* camps. It would improve the model if an additional module were created, where all modules can be run at once and where the scenario parameters can be defined. To do this, the three scenario parameters would have to remain undefined until the end, meaning they would be variables of all functions. This would make it easier to generate results for different diesel peak percentages and ECRs of households, as they have to be redefined manually now.

The Python model uses the csv library to import the input data from CSV files into lists and dictionaries. Each column of the CSV file has to be defined in the Python code. A more professional way to import and use data from CSV files is to use the Pandas library, where the data is copied to a Pandas Dataframe. In this data frame, the values are accessed by calling the column title and the row name (index). This prevents having to define each column of the CSV file in the Python code. It would also make it easier to change, add or remove columns from the input files, as the code would not have to be adjusted for this. However, the csv library approach was still found to be efficient.

Despite these limitations, the model works properly and is still a large improvement compared to KALO 1.0. The running time for *all camps* has been reduced to a few minutes per scenario and the model would be easy to use for external users. The improvements described above are passed on to future research.

5.2. KALO 2.1 – Improvement-related limitations and future research

This section discusses the limitations of the larger model improvements implemented, starting with diesel, followed by grid extension and ending with clean water production.

5.2.1. Diesel

The results of the diesel part of the model, described in Section 4.1.5, showed a spike in LCOE values for diesel peak percentages of 80% and 90% because of unused energy in the system. In reality, unused energy can be stored in the battery for use the next day or even later. However, as KALO 2.1 is a scaling model and not a simulation model, this was outside this research's scope.

A solution to remove the amount of unused energy from the system is to create a loop that reduces the solar PV and battery capacity needed in case there is unused energy. However, it can be debated whether it would make sense to consider the same strategy as in Section 4.1 when the diesel generator covers 80% or 90% of the peak demand. This strategy entails using renewable energy first and fossil fuels last. It is the other way around for diesel peak percentages of 80% or 90%, where diesel is used first and only a small fraction of solar energy is used.

Figure 17 shows that a diesel peak percentage of 70% would still make sense, as the diesel generator only covers the "peak" in the demand. This horizontal line would shift downwards for higher diesel peak percentages, and the diesel generator would also cover the baseload. Because of these arguments, it is recommended to use the KALO 2.1 model for diesel peak percentages up until 70%.

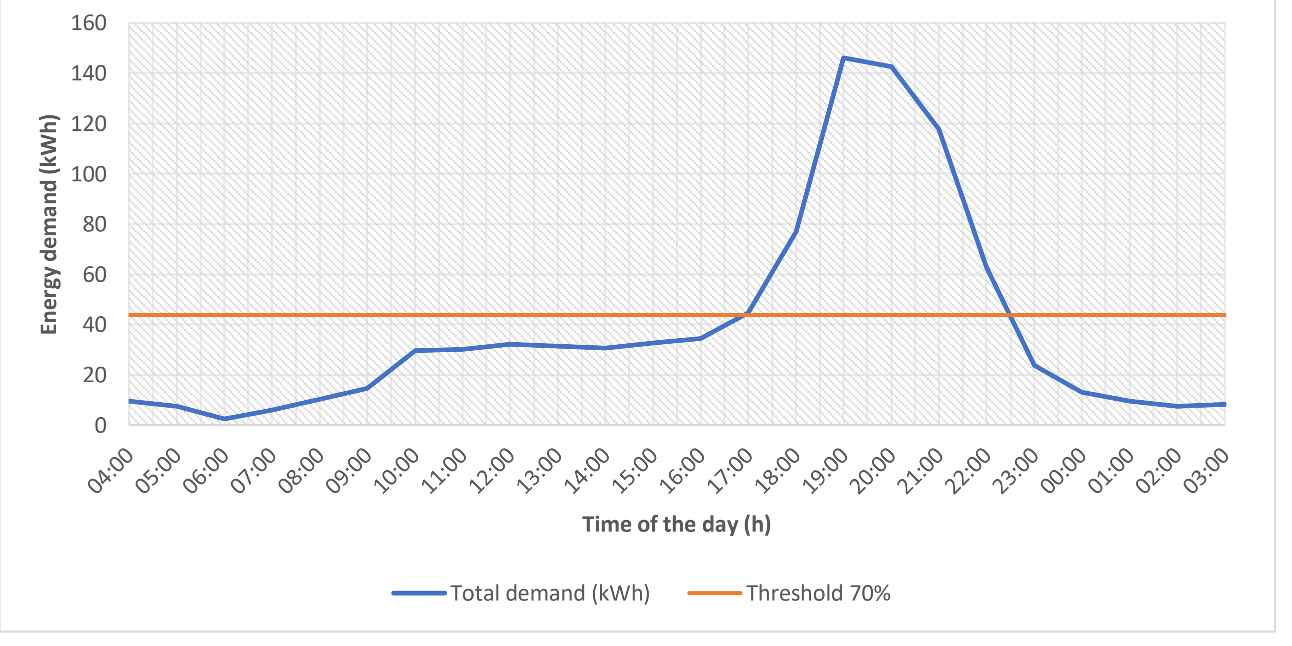

Figure 17. The daily load profile of the Moyo refugee camp in Chad, for a Tier 2 demand scenario and an ECR of households of 100%. The orange horizontal line shows the threshold for which the diesel generator switches on, for a diesel peak percentage of 70%. The demand above this line corresponds to the demand covered by the diesel generator.

The sensitivity analysis shows that the diesel price greatly affects the LCOE. As the diesel prices used from Baldi et al. (2022) did not consider transportation to remote locations, more data on diesel prices that include these transportation costs is needed. In addition, an update of data is needed for financial parameters relating to the diesel generator, such as the replacement time and yearly cost reduction of the generator (assumptions) and the prices of the diesel generator and the fuel tank (Baldi, 2021).

Other useful data that could be collected on all camps would be the capacity and age of the diesel generators that exist in the camps. As of today, Baldi (2021) only reported a generator size of 80 kW in Kalobeyei Village I, in combination with a pre-existing mini-grid. Considering existing diesel generators' capacity would result in a better approximation of the mini-grid's required PV, battery and generator size. As seen in Section 4.1.3, the existing generator capacity is already included in the calculation of the mini-grids generator capacity. The age of the existing generator could affect the generator fuel consumption and load factor. A revision of the technical module would be needed to include this.

Another part of KALO 2.1 that needs to be revised is the calculation of the avoided CO_2 emissions. A reference diesel generator is used to calculate the emission factor of the diesel system in tCO_2/MWh, while an actual diesel generator is modelled as well. More research is needed on how to improve this part of the model.

5.2.2. Grid extension

In the estimation of the upfront cost of transmission lines for grid extension, a general value of 8,000 USD/km was used for all camps. It would improve the model if country-specific costs for transmission lines could be used. Another important limitation of the grid extension module is that grid availability is not considered. To include this, data is needed on grid availability of every country and maybe even on regions within countries, as was seen in the CLOVER model (Philip Sandwell, 2020). Besides the availability of the grid, the sustainability of the electricity from the grid can also be an important factor to consider in the choice between grid extension and a sustainable mini-grid. Data would need to be collected on this topic, as it was not considered in KALO 2.1. From these limitations, it can be concluded that the grid extension module gives only a basic comparison based on costs. However, it gives a nice starting point for further improvements, as described above.

5.2.3. Clean water production

Section 0 shows that the LCOE decreases when water pumping and/or purification is included in the demand. This finding, together with the fact that the access to clean water for refugees is improved, results in the recommendation to include clean water production in combination with a sustainable mini-grid. However, it is important to include the demand for clean water production in the sizing process of the mini-grid. When this is not done, implementing water pumping and/or purification reduces the amount of electricity available for other consumers. Lastly, it is important to point out that the costs of the equipment (and its installation and maintenance) for water pumping and purification are not considered in the model. Additional investments would be necessary to cover these costs.

5.3. KALO 2.1 - General limitations and future research

The KALO-model is a *pre-feasibility* model. It only gives an *estimate* of the size of the required installations. There is high uncertainty in the demand because people come and go in refugee camps. This uncertainty is lower in studies addressing rural areas.

The first step to better include this uncertainty in the model is to include more heterogeneity between households, businesses and institutions within one camp. Firstly, not every household is the same. The consumption of different households could depend on geographical location, but also on the number of people in one household. Secondly, different types of businesses and institutions can be distinguished. For businesses, examples are restaurants, fruit and vegetable stalls, kiosks, electronics stores, clothes and shoe halls, barbers, grocery stores, phone charging stations and tailors. For institutions, examples are healthcare centers, schools and agency offices (Baldi, 2021). Each of these examples would have its own 'typical' load profile.

It would be interesting to collect field-data on the distribution of family sizes within one camp and the difference in their daily load profiles. In addition, collecting field-data in refugee camps should focus on the number of the above-mentioned types of businesses and institutions, and their typical daily load profile. This data can be extended to other camps using a new corrective factor. When this data cannot be collected, a first step would be to include a randomness factor for every consumer type, which distinguishes different types of each consumer. This would create differences between camps with the same number of consumers. This could also be added to the model as an additional corrective factor.

The KALO-model is only a *scaling* model. It creates settlement-specific daily load profiles, which are copied to all other days of the year. The PV, battery and generator capacity are scaled to meet this daily load profile. At this moment, the model is not suitable for simulation, despite the scaling being based on an hourly timestep for one day. The financial module has a yearly timestep. A model improvement would be to include seasonal variation. Location-specific solar irradiation on an hourly basis could be used, as is done in the CLOVER model (Phillip Sandwell, n.d.). The model could be adjusted to perform simulation and optimization instead of just scaling. However, this would require additional research and substantial changes to the model.

More reflection on the LCOE calculation is needed in the future. The LCOE can be calculated using two perspectives, which are a company and a project point of view. If a project perspective is taken on, all agents involved with the project should be included, including banks. The interest on a loan would then be a benefit to the project. However, when a company perspective is used, this interest is a cost. At this moment, the approach is mixed between these two perspectives. It is important to understand who the investor of the project would be, as different investors have different opportunity costs. This affects the discount rates that would be used.

Despite the limitations and recommendations for further research mentioned above, the KALO-model gives useful information about the potential of a mini-grid in different camps. It allows for comparing different locations based on capacity requirements and costs.

5.4. Research-related limitations and future research

This research focused on *building the model* in Python. The focus was not on the update of data. However, it is acknowledged that multiple data have to be updated, as mentioned in the previous paragraphs. In addition, the input data on all camps used from UNHCR2020 needs to be updated.

Lastly, multiple improvements defined at the beginning of this study (Section 3.1) were not incorporated and are passed on to further improvements. The first one is to estimate the length of distribution cables necessary to connect all consumers. Currently, this is not included in the technical part of the model. Only the costs of low voltage distribution cables are included in the financial module and are calculated in USD/connection. It would be better to calculate the costs in USD/km.

The second is to differentiate more financial parameters per country. As was seen in Section 3.2.3, only the electricity tariffs, exchange rates, discount rates and diesel prices are distinguished per country. Other values reported in Table 5 and Table 6 of that section are assumed to be constant for all camps. However, investment costs of technological elements, VAT, Tax and interest rates, and yearly cost reduction of assets must also be distinguished per country. This would improve the outcomes of the model.

Lastly, affordability data generated by (Baldi, 2021) was not used or incorporated into the KALO-model. As this data is recognized to be valuable, more research is needed on how to incorporate this data properly.

6. Conclusion

The aim of this research was: '*Building an open-source pre-feasibility planning model in Python to compute the mini-grid's size in displacement settlements in Sub-Saharan Africa and to compute relevant techno-economic indicators to evaluate alternative configurations, based on scarce input data.*'

The KALO-model is designed specifically to be used for refugee settlements, unlike the HOMER and CLOVER software (see Section 1.3). In contrast to the existing literature, the KALO-model allows performing pre-feasibility studies for multiple camps instead of focusing on one camp. Currently, the model can be run for all 288 camps in the database. The model uses basis camp-specific input data, such as population size and average family size, to approximate the daily load profile of a camp. Extending the load profile of the Kalobeyei refugee camp, which is based on field-data of a pre-existing mini-grid, to other camps was done in the KALO-model and not seen before. In contrast to the literature, KALO allows combining the estimation of the demand, sizing the mini-grid and computing financial indicators in one model.

This research reproduced and improved KALO 1.0 to KALO 2.1 in Python. The computational time per scenario was lowered to only a few seconds for one camp and a few minutes for all camps. The Python model is also less prone to error, as the only manual adjustment the user has to make is defining the scenario. It has a clear structure with five modules, where each module has a structure following input, calculations and output. Three input CSV files are used and one output CSV file is produced per scenario. A sensitivity analysis can be run by simply pressing the play button in that Python module.

In addition, KALO 2.1 allows comparing alternative configurations for electricity access in refugee settlements. It can compare a fully renewable PV-battery mini-grid with levels of hybridization with diesel. These technological alternatives can be compared based on the required capacities of solar PV, batteries and the diesel generator, but also on avoided CO_2 emissions, upfront costs and LCOE. The LCOE has multiple variants, including the LCOE-GenOnly, which only considers generation upfront costs, and the LCOE-WACC, which uses country-specific discount rates. Another technological alternative that can be compared to the mini-grid is grid extension. For this comparison, the generation upfront costs of the mini-grid can be compared to the upfront costs of transmission lines for grid extension. In addition, the LCOE of the mini-grid can be compared to the national electricity tariff.

There are some model outcomes that contribute to knowledge. The LCOE increases for all camps when diesel is used in hybrid form with the sustainable mini-grid. It was also found that for more than ¾ of the camps, grid extension would be a more favorable option than a sustainable mini-grid, in terms of costs. Grid extension was found to be more attractive than a mini-grid for large camps and for camps close to the grid. However, grid availability and sustainability were not considered. Lastly, including the demand for water pumping and purification in refugee camps decreases the LCOE.

The technological alternatives can be compared for all camps in the database. The output of the model gives a scale of the technological effort and the costs needed for different locations. It shows where most (or least) investments are needed and how many people benefit from it. The output is relevant for UNHCR, as they can create pipeline projects and implementation plans per region, based on this data. Lastly, the characteristics required for the model to be open-source are there, but steps of actually sharing it are not taken yet. Eventually, the goal is to make the model open-source.

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Appendices

1. Python concepts

First of all, it is important to explain some important concepts in the Python programming language. A piece of code is written into a Python file. When this file is saved, this file is called a Python **module**. The functionalities that are in the module can be used in any other Python file. These functionalities can include functions and objects, which will be explained later. The use of modules keeps the original code structured and short. Python offers a Standard **Library** that includes a wide range of facilities. These include built-in modules, which can be called directly, or modules that must be imported from the library first (PSF, n.d.-d). The latter can be done using code 1 from Table A. 1. A list of Python modules can be retrieved from the official website of Python (PSF, n.d.-c). There are also third-party modules that are not included in the Standard Library but are written by the big Python community. These can be imported using code 2 from Table A. 1.

The Python Software Foundation describes objects as: "**Objects** are Python's abstraction for data. All data in a Python program is represented by objects or by relations between objects" (PSF, n.d.-a). Every object has an identity, a type and a value. Only the value is changeable. Also, objects are given a name that corresponds to what it represents. The most important built-in data types described by Romano (2018) are:

- A **string** represents textual data and is an immutable object. It is given using quotation marks (see code 3 from Table A. 1).
- A **list** is a mutable sequence that can store a collection of objects. Lists are given using brackets, where the objects are separated by a comma (see code 4 from Table A. 1).
- Like a string and a list, a **dictionary** is a built-in data type in Python. A dictionary is a mutable object that maps keys to values, as shown in code 5 from Table A. 1.

Table A. 1. Examples of pieces of code for Python, including examples.

Piece of code	Explanation
1) from <module_name> import <function_name>	When you want to use a function from a module from the Standard Library or from your own files, where module_name is the name of that specific module and function_name is the name of the function that you want to call from the module.
2) pip install <module_name>	When you want to use a module that is not in the standard library or in your own files.
3) String1 = 'Hello World'	An example of a string.
4) List1 = [1, 2, 3]	An example of a list.
5) Dict1 = {'A' : 1, 'Z' : -1}	An example of a dictionary.
6) def my_function(input): *…* *return output*	An example of a function.
7) camp_name = input('Enter the name of the camp: ') *scenario_name = input("Enter a scenario: ")*	This is how you can demand input from the user.

A **function** stores a piece of code that can be reused anywhere in the code and performs a specific task (Romano, 2018). This is shown with code 6 from Table A. 1.

One of the main tools in Python is the **if statement**. It evaluates an expression and executes the part of the code corresponding to the result. This can be a True or False case (called Boolean), or multiple alternatives for the false result can be given using as many *elif* statements as you want. In addition, there are “for” loops and “while” loops. **For loops** are used to repeat an action for every element in a sequence. This can be a list or a collection of objects. **While loops** repeat an action as long as a specified condition is satisfied. It does not loop over a sequence like the “for” loop. These loops can be included in functions, which can be called later in the code.

Lastly, there is the **input** function, which demands input from the user. This could be useful to let the user choose for which camp Python should generate the results. The code would look like code 7 from Table A. 1. This camp_name and scenario_name can then be used in the rest of the code.

2. Additional information KALO-model

2.1. Demand module

Table A. 2 gives information on the corrective factors used by Baldi (2021) and Baldi et al. (2022).

Table A. 2. The corrective factors used by Baldi (2021) to estimate a camps electricity demand, based on field-data from Kalobeyei refugee camp.

Corrective factor	Value	Description
CF1 Data collection factor	Differs per camp	It linearly extrapolates the fixed daily load profiles from Kalobeyei to any other camp size, for every type of consumer.
CF2 Captive generation factor	0.9879	It prevents oversizing the system, as some refugees already have other energy supply systems and will not use the mini-grid.
CF3 Trend adjuster factor	ECR 80%: 18% ECR 100%: 20%	It accounts for the fact Kalobeyei refugee camp (from which field-data is collected) is already partly connected to a mini-grid.
CF4 Tier 2 factor	2.1490	It increases the energy demand of households in the Tier 2 scenarios to 200 Wh/day. In the Baseline scenarios, this factor equals 1.
CF4 Tier 3 factor	10.7452	It increases the energy demand of households in the Tier 3 scenarios to 1000 Wh/day. In the Baseline scenarios, this factor equals 1.
CF_{bus} Business number factor	0.0507	It estimates the number of businesses present per camp as a fraction of the number of households. It is based on data from 9 camps.
CF_{inst} Institutions number factor	0.0059	It estimates the number of institutions present per camp as a fraction of the number of households. It is based on data from 9 camps.

Corrective factor 1, $CF1_{cons}$, is computed as:

$$CF1_{cons} = \frac{\#cons}{average(N_{Cons,Trend})} * ECR_{cons} \qquad \text{Eq. 47}$$

where $N_{Cons,Trend}$ is the number of households, businesses or institutions per village that were registered during the Kalobeyei data gathering by Baldi (2021) (Kalobeyei assessed households, businesses or institutions reported in Table 1). The average of these three values per type of consumer is used in the calculation of CF1. $\#cons$ is the amount of households, businesses or institutions that belong to the camp for which the calculations are done.

Corrective factor 4, $CF4$, is defined as:

$$CF4 = \frac{average(Dload_{Tier2\ or\ Tier3}(kWh) * N_{hh,Trend})}{average(LP_{Trend,hh}(t))} \qquad \text{Eq. 48}$$

where $Dload_{Tier2}$ corresponds to the daily load of 0.2 kWh for Tier 2 electricity access and $Dload_{Tier3}$ corresponds to the daily load of 1.0 kWh for Tier 3 electricity access. $Dload_{Tier} * N_{hh,Trend}$ should be calculated for each of the three villages, after which the average value is taken in CF4. Note that CF4 takes on a different value for a Tier 2 and Tier 3 demand scenario.

The consumption share per type of consumer, CS_{cons} (%), is computed as:

$$CS_{cons} = \frac{SUM([LP_{cons}(t)])}{SUM([LP_{tot}(t)])} \quad \text{Eq. 49}$$

Where $SUM([LP_{cons}(t)])$ is the daily energy demand of the consumer and $SUM([LP_{tot}(t)])$ is the daily energy demand of households, businesses and institutions together.

The number of connections per type of consumer is defined as:

$$Nr\ connections_{cons} = Nr_{cons} * ECR_{cons} \quad \text{Eq. 50}$$

2.2. Technical module

Table A. 3 gives an overview of the fuel consumption of the reference diesel generator for different generator sizes and load factors. For this study, a generator size of 75 kW and a load factor of 50% were chosen (Baldi, 2021).

Table A. 3. The fuel consumption of the reference diesel generator for different generator sizes and load factors.

	Fuel consumption of generator at different load factors (%) in US gal/h		
Generator size (kW)	**25%**	**50%**	**75%**
75	2.4	3.4	4.6
100	2.6	4.1	5.8
500	11	18.5	26.4

The following calculations are needed to calculate the emissions factor and the avoided emissions.

$$Consumption\ rate\left(\frac{l}{h}\right) = Conversion\ US\ gal\ to\ liter * fuel\ consumption\ generator\left(\frac{USgal}{h}\right) \quad \text{Eq. 51}$$

$$Consumption\ rate\ \left(\frac{kg}{h}\right) = consumption\ rate\left(\frac{l}{hr}\right) * diesel\ density\ \left(\frac{kg}{l}\right) \quad \text{Eq. 52}$$

$$Electricity\ generated(MWh) = \frac{generator\ size(kW) * load\%}{1000} \quad \text{Eq. 53}$$

$$Load(kW) = generator\ size(kW) * load\% \quad \text{Eq. 54}$$

$$Ratio\ fuel\ consumption\left(\frac{kg}{kWh}\right) = \frac{consumption\ rate\left(\frac{kg}{h}\right)}{load(kW)} \quad \text{Eq. 55}$$

$$Fuel\ consumption(ton) = ratio\ fuel\ consumption\left(\frac{kg}{kWh}\right) * electricity\ generated\ (MWh) \quad \text{Eq. 56}$$

$$Energy(TJ) = \frac{fuel\ consumption(ton) * net\ caloric\ value\ diesel\ (\frac{TJ}{Gg})}{1000} \quad \text{Eq. 57}$$

$$CO2\ emissions\ 1h(kg) = energy(TJ) * emission\ factor\ diesel\ (\frac{kg\ CO2}{TJ}) \quad \text{Eq. 58}$$

The emission factor of the reference diesel generator is computed as:

$$Emission\ factor\left(\frac{ton\ CO2}{MWh}\right) = \frac{CO2\ emissions\ 1h(kg)}{electricity\ generated(MWh) * 1000} \quad \text{Eq. 59}$$

The daily peak sun hours, specified for one month, are defined by:

$$Daily\ peak\ sun\ hours_{month} = monthly\ irradiation\ \left(\frac{kWh}{m^2}\right) / \frac{365}{12} \quad \text{Eq. 60}$$

Data on the monthly irradiation (in kWh/m^2) for all 12 months of a year was collected by Baldi (2021) for each camp's location. The monthly irradiation of a camp was divided by the average amount of days in a year (365/12) to derive the daily sun peak hours belonging to that month (see Eq. 60). This was done for every month of the year. The average of these 12 monthly values was taken to derive the average peak sun hours of a camp, used as fixed input for the Python model. This was done for all 288 camps in the database.

2.3. Financial module

Table A. 4 gives an overview of the calculations carried out in KALO 1.0 to compute the LCOE (Baldi, 2021). The functions and concepts used in these calculations are explained below. The constant numerical values were already summed in Section 3.2.3. The generation hours per day of 94.5% corrects for system failures or other issues, reducing the electricity generation over the year (Baldi, 2021).

Table A. 4. Calculations that are necessary to compute the LCOE.

Parameter	Formula	
R_z	$= upfront\ cost_{asset} * (1 - cost\ reduction\ per\ year_{asset} * replacement\ time_{asset})$	Eq. 61
$O\&M_i$	$= O\&M\ rate * total\ Upfront\ cost * (1 + index\ including\ infl\&deval\ year\ on\ year(y))$	Eq. 62
$Insurance_i$	$= Insurance\ rate * closing\ balance_{all\ assets}(y) * index\ including\ infl\&defl\ year\ on\ year(y)$	Eq. 63
VAT_i	$= VAT\ rate * energy\ revenue_{tot}(y)$	Eq. 64
$Interest_i$	$= interest\ rate\ debt * closing\ balance_{debt}(y)$	Eq. 65
TAX_i	$= tax\ rate * earnings\ before\ tax(y)$	Eq. 66
$Land\ lease_i$	$= land\ lease\ cost * index\ including\ inf\&deval\ year\ on\ year(y)$	Eq. 67

Eg_i	$= PV\ system\ size * PSH * generation\ hours\ per\ day * Yday$	Eq. 68

Number of connections existing mini-grid

Needed for: Distribution Upfront cost

The number of connections belonging to an existing mini-grid, $Nr_{con}\ EMG$, is computed as:

$$Nr_{con}\ EMG = \left(1 - \frac{PV\ system\ size}{PV\ system\ size + kWp\ EMG}\right) * (Nr_{hh} * ECR_{hh} + Nr_{bus} * ECR_{bus} + Nr_{inst} * ECR_{inst}) \quad \text{Eq. 69}$$

Yearly demand

Needed for: Energy revenue

The total yearly demand at the start of the project, which entails the demand of households, businesses and institutions (kWh), is computed by:

$$Yearly\ demand_{tot,start} = eff\ demand_{y1} * Yday \quad \text{Eq. 70}$$

where $eff\ demand_{y1}$ is the effective demand in year 1 and $Yday$ are the number of days in a year.

The total yearly demand at any year *y* during the lifetime of the project (kWh) is defined by:

$$Yearly\ demand_{tot}(y) = \begin{cases} Yearly\ demand_{start}, & if\ y = 1 \\ Yearly\ demand_{start}(y-1) * ADG, & if\ 1 < y \leq 6 \\ Yearly\ demand_{start}(y-1), & if\ y > 6 \end{cases} \quad \text{Eq. 71}$$

where *ADG* is the annual demand growth.

The yearly demand per type of consumer (kWh) is defined as:

$$Yearly\ demand_{cons}(y) = \begin{cases} CS_{cons} * Yearly\ demand(y) * Connections\ built\ y1, & if\ y = 1\ and\ cons = households \\ CS_{cons} * Yearly\ demand(y) * Connections\ built\ y2, & if\ y = 2\ and\ cons = households \\ CS_{cons} * Yearly\ demand(y), & Otherwise \end{cases} \quad \text{Eq. 72}$$

where CS_{cons} is the consumption share per type of consumer computed in the demand module. The number of *connections built in year 1 and 2* model the fact that it takes time for all the *households* to connect to the mini-grid. It is assumed that only from year 3 onwards, all households are connected (Baldi, 2021).

Inflation

Needed for: O&M cost and Insurance cost

The local inflation index in year *y* is defined as:

$$local\ inflation\ index(y) = local\ inflation\ index(y-1) * (1 + inflation\ rate_t) \quad \text{Eq. 73}$$

and the local devaluation index in year *y* is computed as:

$$local\ devaluation\ index(y) = local\ devaluation\ index(y-1) * (1 - devaluation\ rate_t) \quad \text{Eq. 74}$$

For each country, the inflation rates of the first four years are known and are used as input in the Python model (see Section 3.2.3). The inflation rate of the fourth year is copied to the other years of the lifetime (= year 5 to year 20). Baldi (2021) did not find devaluation rates and therefore assumed that a devaluation rate would be half the value of an inflation rate. This means that the inflation rate in year *t* is multiplied by a factor of 0.5 to get the devaluation rate in year *t* (see also Table 5 in Section 3.2.3). The local inflation and devaluation indexes in year 1 are equal to 1.

The index including inflation and devaluation year on year, in year *y*, is computed as:

$$index\ including\ infl\&deval\ year\ on\ year(y) = \frac{local\ inflation\ index(y) * local\ devaluation\ index(y)}{local\ inflation\ index(y-1) * local\ devaluation\ index(y-1)} \qquad \text{Eq. 75}$$

Closing balance and depreciation assets

Needed for: Insurance cost (closing balances) and Tax cost (depreciation)

The yearly depreciation (USD) of an asset is defined as:

$$depreciation_{asset}(y) = \frac{investment\ cost_{y,asset}}{replacement\ time_{asset}} \qquad \text{Eq. 76}$$

The investment costs of the asset are equal to the upfront cost made at the start of the simulation period. When the asset is replaced, the investment costs are decreased because the cost of the asset decrease by a specified percentage per year (see Table 5 in Section 3.2.3). The new investment costs are equal to R_z (Eq. 61) and the yearly depreciation is decreased.

The closing balance of an asset in year *y* (USD) is defined by:

$$closing\ balance_{asset}(y) = opening\ balance_{asset}(y) + R_{z,asset} - depreciation_{asset}(y) \qquad \text{Eq. 77}$$

And the opening balance of an asset in year y (USD) is computed as:

$$opening\ balance_{asset}(y) = closing\ balance_{asset}(y-1) \qquad \text{Eq. 78}$$

Note that the replacement of an asset, $R_{z,asset}$, only happens in the year at which the asset is replaced.

The total closing balance in year *y* (USD) is computed by:

$$closing\ balance_{all\ assets}(y) = closing\ balance_{PV\ modules}(y) + closing\ balance_{PV\ inverter}(y) + closing\ balance_{batteries}(y) + closing\ balance_{other\ assets}(y) \qquad \text{Eq. 79}$$

The residual value for the closing balance in year 1 is subtracted from the yearly cost in year 20, as it is assumed that the assets can be sold for their residual value.

Revenue

Needed for: VAT cost (only energy revenue) and Tax cost (both energy and connection charge revenue)

The connection fee revenue (USD) is computed as:

$$connection\ charge\ revenue = connection\ fee\ consumer * (Nr_{con,hh} + Nr_{con,bus} + Nr_{con,inst}) \quad \text{Eq. 80}$$

and only happens at year 1. This is the fee the consumers have to pay for their connection (see Table 5 in Section 3.2.3 for the value).

Besides the connection fee in year 1, the consumers must pay a price per kWh electricity that they consume. National electricity prices collected by Baldi (2021) are used and have to be adjusted to a value in USD. Baldi (2021) also collected exchange rates per country, which are used to do this. National electricity prices were distinguished for households, businesses and institutions. These country-depended values are imported into Python as described in Section 3.2.3.

The electricity tariff per consumer (USD/kWh) is defined as:

$$tariff_{cons} = \frac{national\ electricity\ price\ (currency\ per\ kWh)}{Exchange\ rate\ (curency\ per\ USD)} \quad \text{Eq. 81}$$

Consequently, the yearly energy revenue per consumer (USD) is defined as:

$$energy\ revenue_{cons}(y) = tariff_{cons} * yearly\ demand_{cons}(y) \quad \text{Eq. 82}$$

The total yearly energy revenue, for households, businesses and institutions together (USD), is computed by:

$$energy\ revenue_{tot}(y) = energy\ revenue_{hh}(y) + energy\ revenue_{bus}(y) + energy\ revenue_{inst}(y) \quad \text{Eq. 83}$$

Debt

<u>Needed for: Interest cost</u>

The project is financed with 2% depth, which means that 2% of the upfront cost will be covered by a loan that has to be paid back. The debt repayment period is 11 years. Besides the repayment, interest has to be paid, which is 8% of the residual amount of the loan that still exists in year *y* (Baldi, 2021).

The initial debt drawdown (in USD) is computed by:

$$initial\ debt\ drawdown = project\ cost\ financed\ with\ debt\ (\%) * upfront\ cost \quad \text{Eq. 84}$$

The yearly debt repayment is defined by:

$$repayment_{debt}(y) = \frac{initial\ debt\ drawdown}{repayment\ period_{debt}} \quad \text{Eq. 85}$$

Finally, the closing balance in year *y*, on which the interest cost are calculated, is computed by:

$$closing\ balance_{debt}(y) = opening\ balance_{debt}(y) - repayment(y) \quad \text{Eq. 86}$$

and the opening balance in year *y* is defined as:

$$opening\ balance_{debt}(y) = closing\ balance_{debt}(y-1) \tag{Eq. 87}$$

Earnings before tax

Needed for: Tax cost

The earnings before tax (USD) in year t are computed as:

$$\begin{aligned} earnings\ before\ tax(y) \\ &= energy\ revenue_{tot}(y) + connection\ charge\ revenue_{t1} - O\&M(y) \\ &- insurance(y) - land\ lease(y) - interest\ expense(y) \\ &- depreciation(y) \end{aligned} \tag{Eq. 88}$$

The connection charge revenue is only added in Eq. 88 in year 1. Tax is only paid when the earnings before tax are larger than zero (Baldi, 2021).

3. The demand for solar PV and Batteries in a hybrid system with diesel

The sum of the two yellow cells, $S_{init,tot}$ and $CH_{B,solar,tot}$, is the demand to which the solar PV installation is scaled. The blue cell, $DisCH_{B,tot}$, is the demand to which the battery capacity is scaled. Only when the blue cell, $DisCH_{B,tot}$, is larger than the orange cell, $CH_{B,diesel.tot}$, the battery needs to be charged with solar energy, $CH_{B,solar}$. That is the case for a diesel peak percentage of 30%, but not for a diesel peak percentage of 90%.

Table A. 5.The values behind Figure 6 from Section 4.1.3. The numbers are given for the Moyo refugee camp in Chad, for a Tier 2 demand scenario, an ECR of households of 100% and a diesel peak percentage of 30%.

Vector	LP_{tot}	LP_{SB}	LP_D	$LP_{D,N}$	Ex_D	$CH_{B,diesel}$	S_{init}	$DisCH_B$	$CH_{B,solar}$
Eq.					$LP_{D,N} - LP_{tot}$	Ex_D if $Ex_D > 0$; 0 Otherwise	$-Ex_D$ if $Ex_D < 0$; 0 Otherwise	$-Ex_D$ if $Ex_D < 0$; 0 Otherwise	$CH_{Trend,t} * (DisCH_{B,tot} - Ex_{D,tot})$
Notes		10% of peak	90% of peak	Minimum 35% load			Only during the day	Only at night	Only if $DisCH_{B,tot} > CH_{B,diesel,tot}$
Hour									
4	9.64	9.64	0	0	-9.64	0	0	9.64	0
5	7.48	7.48	0	0	-7.48	0	0	7.48	0
6	2.49	2.49	0	0	-2.49	0	0	2.49	0
7	6.04	6.04	0	0	-6.04	0	1.81	4.23	0
8	10.38	10.38	0	0	-10.38	0	7.27	3.11	0
9	14.71	14.71	0	0	-14.71	0	14.71	0	27.65
10	29.54	29.54	0	0	-29.54	0	29.54	0	46.09
11	30.23	30.23	0	0	-30.23	0	30.23	0	50.69
12	32.10	32.10	0	0	-32.10	0	32.10	0	70.51
13	31.36	31.36	0	0	-31.36	0	31.36	0	72.35
14	30.61	30.61	0	0	-30.61	0	30.61	0	64.52
15	32.79	32.79	0	0	-32.79	0	32.79	0	55.30
16	34.61	34.61	0	0	-34.61	0	34.61	0	36.87
17	44.67	44.67	0	0	-44.67	0	44.67	0	27.65
18	76.95	76.95	0	0	-76.95	0	53.86	23.08	0
19	146.13	102.29	43.84	43.84	-102.29	0	30.69	71.60	0
20	142.67	102.29	40.38	40.38	-102.29	0	0	102.29	0
21	117.62	102.29	15.33	15.40	-102.22	0	0	102.22	0
22	63.11	63.11	0	0	-63.11	0	0	63.11	0
23	23.71	23.71	0	0	-23.71	0	0	23.71	0
24	13.25	13.25	0	0	-13.25	0	0	13.25	0
1	9.62	9.62	0	0	-9.62	0	0	9.62	0
2	7.48	7.48	0	0	-7.48	0	0	7.48	0
3	8.31	8.31	0	0	-8.31	0	0	8.31	0
Total	925.49	825.95	99.54	99.62	-825.88	0	374.25	451.63	451.63

Table A. 6. The values behind Figure 7 from Section 4.1.3. The numbers are given for the Moyo refugee camp in Chad, for a Tier 2 demand scenario, an ECR of households of 100% and a diesel peak percentage of 90%.

Vector	LP_{tot}	LP_{SB}	LP_D	$LP_{D,N}$	Ex_D	$CH_{B,diesel}$	S_{init}	$DisCH_B$	$CH_{B,solar}$
Eq.					$LP_{D,N} - LP_{tot}$	$Ex_D\ if\ Ex_D > 0$ $0\ Otherwise$	$-Ex_D\ if\ Ex_D < 0$ $0\ Otherwise$	$-Ex_D\ if\ Ex_D < 0$ $0\ Otherwise$	$CH_{Trend,t} * (DisCH_{B,tot} - Ex_{D,tot})$
Notes		10% of peak	90% of peak	Minimum 35% load			Only during the day	Only at night	Only if $DisCH_{B,tot} > CH_{B,diesel,tot}$
Hour									
4	9.64	9.64	0	0	-9.64	0	0	9.64	0
5	7.48	7.48	0	0	-7.48	0	0	7.48	0
6	2.49	2.49	0	0	-2.49	0	0	2.49	0
7	6.04	6.04	0	0	-6.04	0	1.81	4.23	0
8	10.38	10.38	0	0	-10.38	0	7.27	3.11	0
9	14.71	14.61	0.09	46.20	31.49	31.49	0	0	0
10	29.54	14.61	14.93	46.20	16.66	16.66	0	0	0
11	30.23	14.61	15.61	46.20	15.97	15.97	0	0	0
12	32.10	14.61	17.49	46.20	14.10	14.10	0	0	0
13	31.36	14.61	16.75	46.20	14.84	14.84	0	0	0
14	30.61	14.61	15.99	46.20	15.59	15.59	0	0	0
15	32.79	14.61	18.18	46.20	13.41	13.41	0	0	0
16	34.61	14.61	20.00	46.20	11.59	11.59	0	0	0
17	44.67	14.61	30.06	46.20	1.53	1.53	0	0	0
18	76.95	14.61	62.33	62.33	-14.61	0	10.23	4.38	0
19	146.13	14.61	131.52	131.52	-14.61	0	4.38	10.23	0
20	142.67	14.61	128.05	128.05	-14.61	0	0	14.61	0
21	117.62	14.61	103.00	103.00	-14.61	0	0	14.61	0
22	63.11	14.61	48.49	48.49	-14.61	0	0	14.61	0
23	23.71	14.61	9.10	46.20	22.49	22.49	0	0	0
24	13.25	13.25	0	0	-13.25	0	0	13.25	0
1	9.62	9.62	0	0	-9.62	0	0	9.62	0
2	7.48	7.48	0	0	-7.48	0	0	7.48	0
3	8.31	8.31	0	0	-8.31	0	0	8.31	0
Total	922.39	293.22	629.22	888.66	9.91	157.67	23.69	124.07	0