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Optimized Renewable Energy Systems for Self-Sufficient Village

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ABSTRACT

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As Green renewable energy is becoming more relevant, it imposes a new set of problems in system sizing. This bachelor thesis was done with the fresh branch of EFS GmbH, EFS.Greentech to tackle this problem. A decentralized green energy system can offer a level of self-sufficiency and lower the carbon footprint of a village. In this project, the goal is to develop a modular simulation model that can optimize the energy system of residence cluster. There are four main components in the model are a wind turbine, a photovoltaic system, a battery, and a load. The model is driven by weather datasets, energy load profiles and optimizable parameters.

The results of the optimization are a guideline for theoretical energy solutions and show that the model works as intended while offering an oversight on possible energy system sizes at different self-sufficiency levels. With further refinement this model can become a reasonable energy solution sizing tool for reality. The flexibility and simplicity of the model allow for modular configuration of the demand and supply components.

Keywords: Renewable Energy System, Simulation, Optimization, Self-sufficiency, Weather Data

ABBREVIATIONS AND SYMBOLS

Abbreviation	Description	Unit
GmbH	Gesellschaft mit beschränkter Haftung, eng. „Company with Limited Liability“	
PV	Photovoltaic	
WT	Wind Turbine	
BT	Battery	
AST	Apparent Solar Time	hh:mm
ET	Equation of Time	Minutes
SOC	State of Charge	
DOD	Depth of Discharge	
OM	Operation and Maintenance Cost	USD/m²/year, USD/Wh/year
UME	Unmet Energy Percentage	%

Symbol	Description	Unit
P	Power	W
G	Global Inclined Irradiation	W/m²
A	Area	m²
η	Efficiency	%
δ	Declination Angle	Degrees
N	Day of the Year	Day
h	Hour Angle	Degrees
θ	Solar Incidence Angle	Degrees
L	Latitude	Degrees
β	Tilt Angle of the Panel	Degrees
Z_s	Surface Azimuth Angle	Degrees
Φ	Solar Zenith Angle	Degrees
R_b	Beam Radiation Tilt Factor	-

ρ_g	Ground Reflectance Albedo	-
H	Horizontal Irradiation	W/m²
T	Temperature	˚C, K
v	Velocity	m/s
h	Height	m
z_0	Roughness Length	m
ρ	Air Density	Kg/m³
$R_{specific}$	Specific Gas Constant	J/kgK^{-1}
Q	Battery Capacity	Wh
I	Initial Cost	USD
α	Per-unit Cost	USD/m², USD/Wh
N_p	Lifespan	Year
ν	Inflation Rate	Percentage
γ	Loan Interest Rate	Percentage
E	Total Energy Demand	Wh
u	Upper Bound	

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1 INTRODUCTION

This thesis was a project made for the new branch of EFS GmbH, EFS.Greentech. EFS-auto or Elektronische Fahrwerksysteme GmbH is a Joint Venture between the AKKA Industry Consulting and CARIAD SE. EFS was originally founded in 2009 as a joint venture of Audi and Gigatronik in Augraben, Germany. EFS.Greentech was formed in 2021 to expand the company's reach into the green technologies sector. Now EFS operates from three locations in southern Germany, with the headquarters being in Ingolstadt. As of 2022 the company has the headcount of over 600 with net sales of 3 million euros in 2020 (1). The presented project was developed with the collaboration of the virtual development and "intelligent driving systems" departments.

The goal of this project was to produce a modular simulation model of self-sustainable residences that can optimize the needed energy system. Main components of this model are a wind turbine, a photovoltaic system, a battery and a load. The inputs for the simulation are weather datasets, energy load profiles and optimizable parameters. This work uses the software tools, that the company normally uses in the automotive industry, in a project for a different field of engineering. These forementioned tool being mostly MATLAB, Simulink and MATLAB optimization. The resolution of this model at its current state is one hour, with the total simulation time of one year. The model calculates the energy resources from the given weather data with basic power generation formulas avoiding the dynamics in some parts of the systems. These energy resources are then coupled with the operation of the battery to satisfy the energy demand. This model can be used to size the electrical energy systems for many purposes, for example a self-sustainable residence, an off-the-grid sensor station or a field hospital.

Chapter 2 focuses on the modelling of the energy systems, going into detail on what approach was chosen to model these systems. Chapter 3 includes the optimization problem of the simulation, and chapter 4 goes through the optimized results of a scenario that was simulated with the model.

2 RENEWABLE ENERGY SYSTEMS

The complete simulation model consists of four components. These components are photovoltaic *(PV)*, wind turbine *(WT)*, battery *(BT)* and the energy load profile. Power generation components, PV and WT calculate the available electrical energy resource from weather data. These power generation components are then connected to the load in parallel with the battery. Next subchapters 2.1 – 2.5 go through all of the fore mentioned components and how do they operate together.

2.1 Photovoltaics

The sun is the main provider of radiation energy for Earth. This radiation keeps the surface of our planet warm enough to support life. With modern technology it is possible to turn this radiation into different more useful forms of energies, mostly thermal- and electrical energy.

Photovoltaics is the most common form of turning solar radiation into electrical energy (2). Photovoltaics work by utilizing semiconductive materials. These materials can experience the photovoltaic effect, where a photon is absorbed and transformed into electrical potential and current. This technology gives us a way to harvest the abundant solar energy.

A photovoltaic system is a great source of renewable electrical energy. The system is highly scalable, requires no fuel and minimal maintenance. Photovoltaics can also function as an independent system without a grid connection, this makes it a good candidate for our purposes.

The amount of electricity that the system can produce is the product of global inclined radiation, the area of the photovoltaics, the efficiency of the photovoltaic and the efficiency of the power converters. This can be expressed as

$$P_{PV}(t) = G(t) * A_{PV} * \eta_{PV} * \eta_{Con} \qquad \textit{(FORMULA 1)}$$

where

$P_{PV}(t)$ = Output Power of the PV,

$G(t)$ = Global Inclined Radiation,

A_{PV} = Area of the Photovoltaic Installation,

η_{PV} = Efficiency of the Photovoltaics,

η_{Con} = Efficiency of the Power Conversion.

2.1.1 Inclined Radiation Estimation

The radiation on the tilted surface is estimated from the global horizontal radiation data provided by the weather stations. This estimation is done for each measurement and is dependent on the combined position of the sun and the earth, with the time and geometry of the installed solar system. Estimating the radiation on a tilted surface requires us to correct the suns position in the measured weather data. This correction can be applied by calculating the declination angle for the whole year. Declination angle δ is the angle between the equator and the centre of the sun. This value is not constant, since the earth tilts on its axis hence the angle changes with a yearly cycle. The declination angle is estimated from the day number of the year with,

$$\delta = 23.45° \, sin \left[\frac{360}{365}(N + 284)\right] \qquad \textit{(FORMULA 2)}$$

where,

N = The day of the year.

The weather data uses the time of the location's time zone. We can correct this longitude time error into apparent solar time or AST with the use of local standard time, standard longitude, local longitude and the equation of time (3). The latter part of the formula is either added or subtracted depending whether the location is on the east or west side of the standard longitude meridian

$$AST = LST + ET \pm 4(SL - LL) \qquad \textit{(FORMULA 3)}$$

where

AST = Apparent Solar Time

LST = Local Standard Time,

ET = Equation of Time,

SL = Standard Longitude,

LL = Local Longitude.

The equation of time takes the nonregularities of the earth's orbit around the sun into account. This value can be approximated by the day of the year using the following formula

$$ET = 9.87\, sin(2B) - 7.53\, cos(B) - 1.5\, sin(B) \qquad \textit{(FORMULA 4)}$$

where

ET = Equation of Time,

and term B is defined by

$$B = (N - 81)\frac{360}{364} \qquad \textit{(FORMULA 5)}$$

where

N = Day of the Year.

The correction is calculated for each day of the year, this can be seen visualized in the figure 1.

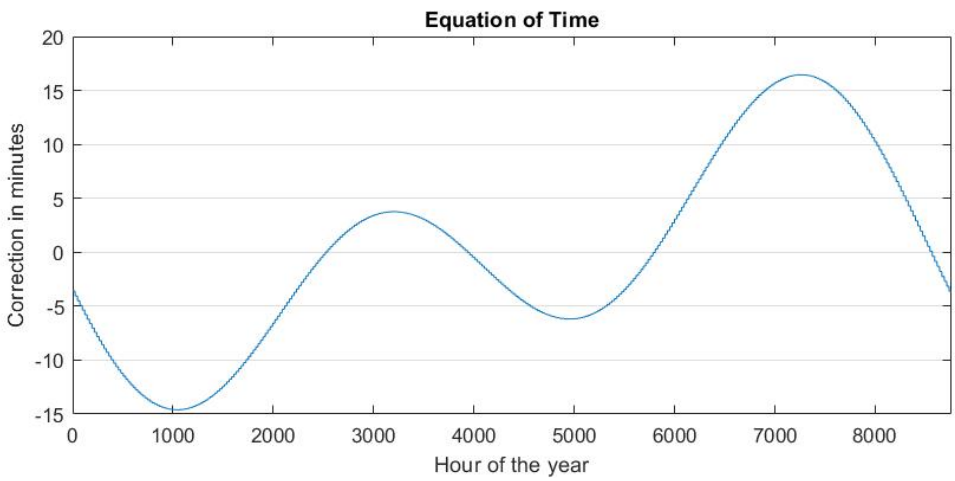

FIGURE 1. Visualization of equation of time.

The Hour Angle is an angle between two planes, the first plane is defined by the North pole, South pole and the point on the surface of the Earth we are inspecting. The second plane is defined by the North pole, South pole and the middle point of the sun. This angle can be calculated with the Apparent Solar Time with the formula:

$$h = (AST - 12)15 \qquad \textit{(FORMULA 6)}$$

Solar Incidence Angle is the angle between the sun's rays and the normal of the collector's plane. With perfect full tracking system this angle would be zero. Non-reduced form of the formula was used to keep the flexibility of the model.

$$\begin{aligned} cos\,\theta = {} & sin\,L\,sin\,\delta\,cos\,\beta - cos\,L\,sin\,\delta\,sin\,\beta\,cos\,Z_s \\ & + cos\,L\,cos\,\delta\,cos\,h\,cos\,\beta + sin\,L\,cos\,\delta\,cos\,h\,sin\,\beta\,cos\,Z_s \\ & + cos\,\delta\,sin\,h\,sin\,\beta\,sin\,Z_s \end{aligned}$$

(FORMULA 7)

where

θ = Solar Incidence Angle,

L = Latitude,

δ = Declination Angle,

β = Tilt Angle of The Panel,

Z_s = Surface Azimuth Angle,

h = Hour Angle.

The optimal tilt angle of the panel can be determined with iteration. By changing the value of the angle and observing the change in the inclined radiation, it is possible to get an optimal angle. However, for this thesis the optimal tilt angle was configured using external tools, mainly Photovoltaic Geographical Information System (4).

The Solar Zenith Angle is the angle between the incoming sun's rays and the vertical. This angle represents the horizontal plane of the measurement instrument used at weather stations to collect horizontal irradiation data. The Solar Zenith Angle is calculated by

$$cos\,\phi = sin\,L\,sin\,\delta + cos\,L\,cos\,\delta\,cos\,h \qquad \textit{(FORMULA 8)}$$

where

ϕ = Solar Zenith Angle,

L = Longitude,

δ = Declination,

h = Hour Angle.

From these previously calculated angles, we can calculate a correction factor R_b, that we can apply to horizontal radiation to estimate the radiation on a tilted plane

$$R_b = \frac{cos\,\theta}{cos\,\phi} \qquad \textit{(FORMULA 9)}$$

where

R_b = Beam Radiation Tilt Factor,

θ = Solar Incidence Angle,

ϕ = Solar Zenith Angle.

This radiation tilt factor can then be applied to the horizontal radiation data that the weather station provides

$$G_{Bt} = G_B R_B \qquad \textit{(FORMULA 10)}$$

where

G_{Bt} = Beam Radiation on a Tilted Surface,

G_B = Beam Radiation on Horizontal Surface,

R_B = Beam Radiation Tilt Factor.

2.1.2 Ground Reflectance

The Ground Reflectance Albedo ρ_g is a value that signifies the reflectance of the surfaces surrounding area. This value is chosen for each month and is highly dependent on the location of the site.

Table 1. Surface Albedo values(5).

Surface	Albedo / Reflectivity
Dry dark soil	0.13
Grass	0.17-0.28
Dry sand	0.35
Dune sand	0.37
Old snow	0.4-0.7
Fresh snow	0.75-0.95

Albedo can be estimated by weather and location data. Using the research article (6) as a guide, we can test our simulation by using their Albedo values in our initial testing. The authors of the paper have local experience of the surrounding area and estimate the albedo values as follows:

Table 2. Albedo values.

Month	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
$\boldsymbol{\rho_g}$	0.8	0.8	0.8	0.5	0.2	0.2	0.2	0.2	0.2	0.4	0.8	0.8

The amount of reflected radiation is estimated with forementioned Albedo value, the tilt of the panel and horizontal irradiation by

$$G_R = H\,\rho_g\left(\frac{1-\cos\beta}{2}\right) \qquad \textit{(FORMULA 11)}$$

where

G_R = Ground Reflected Irradiation,

H = Horizontal Irradiation,

ρ_g = Albedo,

β = Tilt Angle of the PV Panel.

2.1.3 PV Cell Temperature and Efficiency

The efficiency of the solar cell changes with its temperature, this factor is known as the temperature coefficient, and is expressed by unit $\%/°C$. This coefficient is unique to every model of panels and varies for each cell type. A typical value for a commercial solar panel is -0.5%/˚C. The nominal efficiency of a solar cell is tested by the manufacturer in standard testing conditions (STC) at 25˚C, 1000W/m^2 and AM1.5 air mass. This means that the efficiency of a Mono-Si solar cell is 15% only at these conditions (7). We can calculate the new efficiency by

$$\eta_{PV} = \eta_{PV_{STC}} - 0.5\%(T_{cell} - 25°C) \qquad \textit{(FORMULA 12)}$$

where

η_{PV} = Temperature Compensated Efficiency,

$\eta_{PV_{STC}}$ = Efficiency of the PV cell at STC,

T_{cell} = Estimated Temperature of the PV cell.

Simulation of the temperature of the cell is a complicated task. This estimation would require deep knowledge of the environment, thermal characteristics and a fluid dynamic analysis of the panel. To simplify this parameter, it was opted to link the irradiation and cell temperature into a simple variable. This temperature change is respective to the ambient temperature T_{amb}.

Table 3. PV Cell Temperature Estimation with Irradiation.

Irradiation	**Solar Cell Temperature T_{cell}**
< 200 W/m^2	T_{amb}
200-400 W/m^2	T_{amb} + 5˚C
400-600 W/m^2	T_{amb} + 10˚C
> 600 W/m^2	T_{amb} + 20˚C

Conversion Efficiency η_{Con} of a PV system consists of the inverter/converter needed to convert the DC power produced by the PV system into AC power that is used in residential buildings. These converters are highly efficient for high class models losing under 1% of the power in the conversion. More ordinary systems have efficiencies of 95% (8).

2.1.4 Implementation

In order to implement this model of a PV system, we need to configure input, output and a set of parameters. The input for the model is horizontal irradiation data from a weather station. This horizontal irradiation is first checked and processed for errors. After processing the data, the horizontal irradiation is then calculated into tilted irradiation by

$$G = G_{Bt} + G_R \qquad \textit{(FORMULA 13)}$$

where
G = Estimated Global Inclined Irradiation,
G_{Bt} = Beam Radiation on a Tilted Surface,
G_R = Ground Reflected Irradiation.

Another input for the PV calculations is the ambient air temperature. These temperature measurements are readily available from weather datasets. With the temperature data we can estimate the PV cell temperature and the temperature affected efficiency of the PV panel. The largest factor that changes the output power of a PV system is the area of the PV cells. The PV-area is a design parameter in the scope of the optimization. It can be increased or decreased to meet certain objectives, e.g., to absorb more solar energy or to reduce the cost of the complete system, respectively.

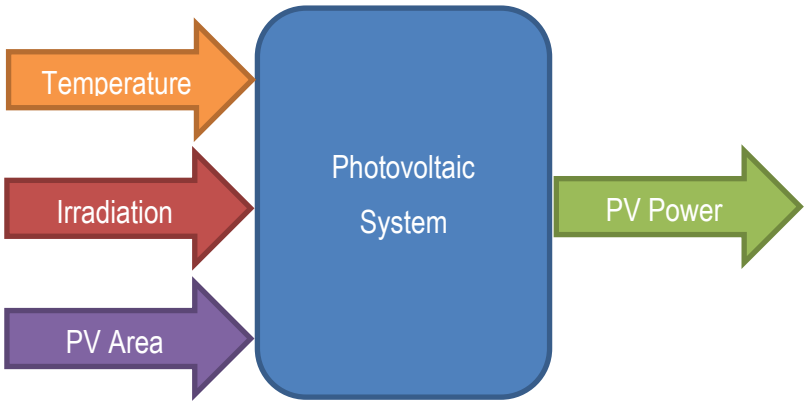

FIGURE 2. Photovoltaic System

2.2 Wind Turbine

Wind power is the second most used renewable electricity source (9), bested by hydropower. Hydropower is excellent on large scale, but has disadvantage when flexibility of location is taken in consideration. Wind is abundant and widespread energy resource that has been taken advantage of for hundreds of years. Modern wind power is mostly generated in the form of electrical power with the help of wind turbines. These turbines transform the kinetic energy of the wind into rotational energy. This rotational energy is then able to drive a generator. The amount of wind energy available is dependent on wind speed. Wind speed is affected by the surrounding environment, hence wind turbines tend to be high above the terrain and/or offshore. Modern wind turbines are mostly constructed out of a concrete foundation, steel tube and composite blades. The internal components like the large generator also require a substantial amount of copper. The current advancements in computer simulations and turbine design enable a steady increase in the average capacity, hub height and rotor diameter of wind turbines. According to the U.S. Department of Energy Land-Based Wind Market Report: 2021 (10) the average onshore wind turbine located in the US in 2019 would have a nominal capacity of 2.5 MW, hub height of 90 meters and rotor diameter of 120 meters.

It is a challenging task to create an accurate model of a wind turbine. This is due to the complex fluid dynamics that take place at the blades. To get around this problem, it was decided to make a few simplifications to the wind turbine simulation model. These simplifications include exclusion of inertia, rotating speed and the yaw degree of freedom. Hence, the model is an ideal wind turbine

that can be used to calculate the available power from the wind speed, given the parameters of the turbine.

The data provided by weather stations usually contain a gust wind speed and mean wind speed for 10 minute and 60 minute intervals measured at a reported height. To estimate the wind speed at the height of the hub, we need to apply formula 14 to the wind speed data

$$v_h = v_{ref} \frac{ln(h/z_0)}{ln(h_{ref}/z_0)} \qquad \textit{(FORMULA 14)}$$

where

v_h = Wind speed at the Height h,

v_{ref} = Wind speed at the Refence Height,

h_{ref} = Reference Height of the Measured Wind speed,

h = Desired Wind speed Height or Hub Height,

z_0 = Roughness Length of the Terrain.

The roughness length of the terrain is a representation of the surrounding areas effect on the wind speed. Lower z_0 value means less obstacles for the wind and higher value means complex topology of the area that the air is passing through, for example z_0 value for lawn grass is 0.008m, field of crops is 0.05m, forest is 0.5m and a city center with tall buildings is 3.0m (11).

The power that the wind turbine can get from the available wind is determined by few parameters. These parameters include the operational wind speed range, the efficiency, air properties and the sweeping area of the turbine blades. The operational wind speed range of a wind turbine are listed as cut-in (v_{ci}), rated (v_r) and cut-out wind speed (v_{co}). The wind speed data is then compared to these parameters and the power generated by the wind turbine is calculated as

$$P_{WT}(t) = \begin{cases} 0 & v(t) < v_{ci} \text{ or } v(t) > v_{co} \\ 0.5\rho v^3 A_{WT}\eta_{WT}\eta_{ConvWT} & v_{ci} < v(t) < v_r \\ P_{rated} = A_{WT} * P_{specific} & v_r < v(t) < v_{co} \end{cases} \qquad \textit{(FORMULA15)}$$

where

P_{WT} = Output Power of the Wind Turbine [W],

ρ = Air Density [kg/m^3],

v = Wind speed [m/s],

η_{WT} = Efficiency of Wind Turbine [%],

η_{ConvWT} = Efficiency of Wind Turbine Converters [%],

P_{rated} = Rated Power of the Wind Turbine [W],

A_{WT} = Sweeping Area of the Wind Turbine [m²],

$P_{specific}$ = Specific Power of the Turbine [W/m²].

The density of air depends on temperature and pressure and is expressed as

$$\rho = \frac{p}{R_{specific}T} \qquad \textit{(FORMULA 16)}$$

where

ρ = Air Density [kg/m^3],

p = Absolute Air Pressure [Pa]

$R_{specific}$ = Specific Gas Constant of Dry Air [287.058 J/kgK^{-1}],

T = Temperature [K].

2.3 Energy Storage

The main disadvantage of renewable energy sources like wind and solar is their intermittency. In order to use these sources to the greatest extend, an energy storage is needed. Energy storages come in many forms such as fly wheels, pumped hydro, thermal mass and electrochemical storage. For residential buildings the most common electrical energy storage is batteries (12). Batteries offer a maintenance free and easily scalable storage solution. There are many uses for a battery in a residential building with a grid connection. For a building without grid connection the storage purpose is mainly to store the produced intermitted energy so that it is steadily available at all hours. The main parameter for a battery is its capacity. The capacity of a battery determinates the amount of energy that can be stored in it. Battery systems come in a variety of shapes and sizes, ranging from a briefcase to a shipping container (13).

For our simplified battery model, we have a State Of Charge parameter or SOC. SOC describes the capacity used and available of the battery. While the battery is full the SOC is equal to 1. The

minimum value of the SOC is determined by the Depth-Of-Discharge DOD. DOD is the range of which the battery is being used. With a DOD of 100% the battery's nominal capacity would be fully utilized. To minimize the degradation of the battery, a lower DOD should be practised.

To calculate the State-Of-Charge, we need to take in account the previous SOC, usable capacity of the battery, power flow through the battery and the duration. From these we can form formula

$$SOC(t) = SOC(t-1) \pm \frac{P(t)\Delta t}{Q} \qquad \textit{(FORMULA 17)}$$

where

$SOC(t)$ = State-Of-Charge at Time t,

$P(t)$ = Power at Time t,

Δt = Duration of Timestep t,

Q = Usable Capacity of the Battery.

The latter term of formula 17 is positive when the battery is charging and negative while discharging. In parallel operation with energy generation and demand the battery operates as shown in figure 3.

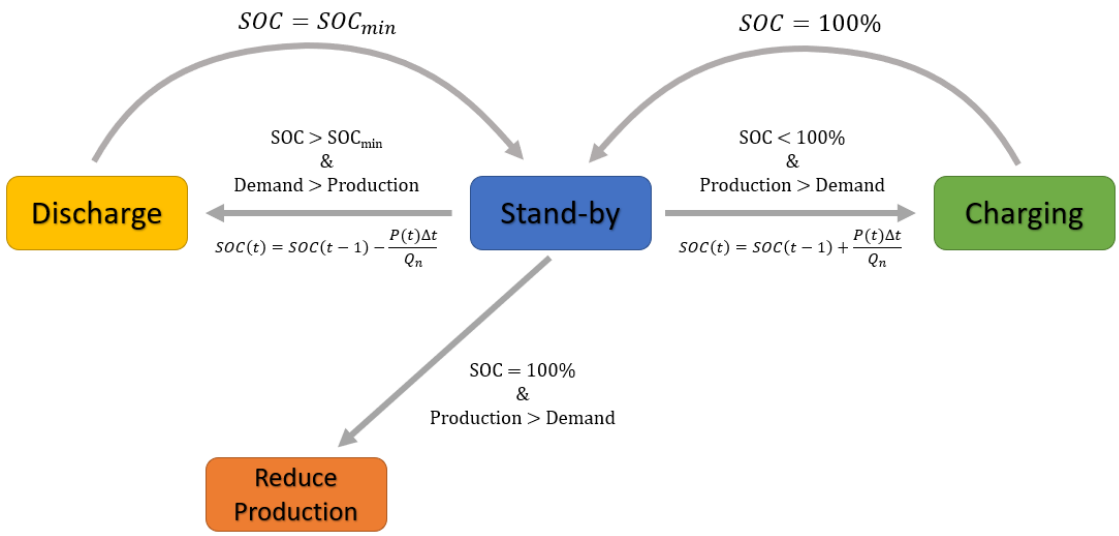

FIGURE 3. Flow diagram of battery operation

2.4 Energy Load Profile

Load profiles reflect the amount of energy needed over given time and can contain data from a singular appliance or describe the complete energy flow of a residential building or a country (14). These profiles can be collected data, generated through stochastic models (15) or generated using a load profile generator (16). For our model we chose to use electrical residential load data collected from southern Germany with hourly resolution. This data is part of an Open Power System Data that provides different types of power related datasets for research purposes. For this project the most useful dataset is the power imported from the grid, since with this information we can estimate the required size of the power generation systems (17).

Data from the forementioned source is expressed as cumulative power over a time period. In order to have the most complete datasets, it was chosen to use the data with one hour resolution. This data was converted from cumulative power to power at an hour. This left us with four complete load profiles, shown in figure 4, that span the year 2016 showing the amount of power consumption at each hour of the year.

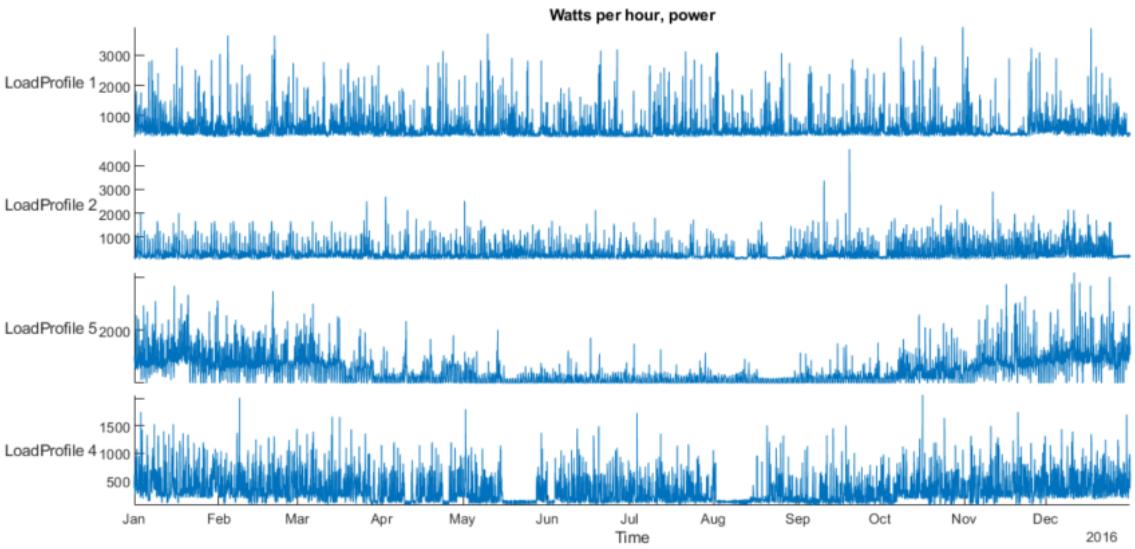

FIGURE 4. Visualized Load Profiles

In order to estimate the electrical energy consumption of a whole village, these load profiles are combined and multiplied to represent a village of 40 houses. This results to a total of 144000kWh,

or 3600kWh per household per year. In contrast a 2–3-person household in Germany uses roughly 3500kWh/year (18).

2.5 System Configuration

The configuration of the model has been kept simple by design and it has three main parts as seen in figure 5. These parts are power generation, energy storage and power demand. For this thesis the power generation units include a photovoltaic system and a wind turbine system. These systems generate power that is then combined and directed to the demand. The energy storage is connected in parallel with the power demand and is operated regarding the difference of the supply and demand as seen in figure 3. This simple and modular design allows us to exchange the models for more complex ones if required, it also makes the development process easier.

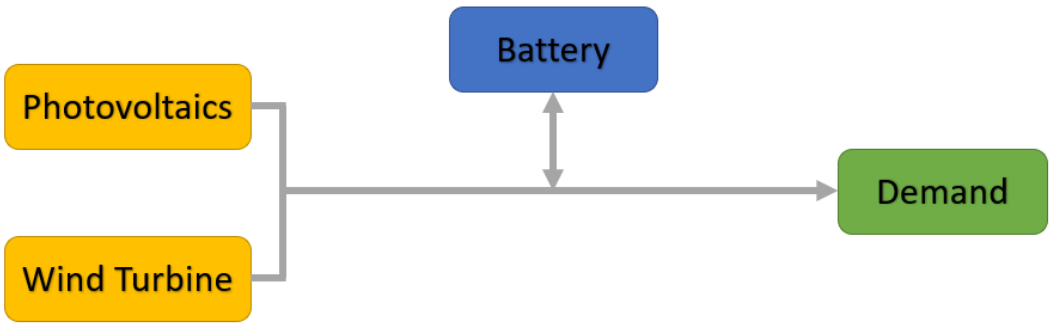

FIGURE 5. Configuration of the System

3 OPTIMIZATION PROBLEM

An optimization algorithm is used to get the optimal sizing of the systems. The model calculates the power flow through the system at each timestep. This power flow is greatly dependant on the weather data and handful of design parameters. The parameters are area of the photovoltaics A_{PV}, sweeping area of the wind turbine A_{WT} and capacity of the battery Q_{BT_CAP}. By varying these parameters, it is possible to get an adequate energy system for the inspected location. This chapter explores the relationship between optimization and the parameters.

In order to optimize, an objective function has to be defined. Since the goal of the optimization is to move towards self-sufficiency of our energy system for a given energy demand, the chosen objective is to minimize the unmet energy (UME) demand. Formula for UME can be interpreted as how much of the energy needs were met per time step, in contrast to the energy needs E over the observed time period.

The second optimization goal is to minimize the cost of the energy system. The cost function consists of initial cost I, operational and maintenance cost OM, loan interest rate γ and inflation rate ν for each system. The initial cost for photovoltaics (I_{PV}) and wind turbine (I_{WT}) can be formulated as

$$I_i = \alpha_i A_i,\ i = PV, WT \qquad \textit{(FORMULA 18)}$$

where

I_i = Initial Cost of a System,

α_i= Per-unit cost of the System [USD/m^2],

A_i= Inspected Area of the System.

The operational and maintenance costs are given by

$$OM_i = \alpha_{OM_i} A_i \sum_{j=1}^{N_p} \left(\frac{1+\nu}{1+\gamma}\right)^j,\ i = PV, WT \qquad \textit{(FORMULA 19)}$$

where

OM_i= Operation and Maintenance Cost,

α_{OM_i}= Yearly per-unit Operation and Maintenance Cost of the System [USD/year/m^2],

A_i = Inspected Area of the System,

N_p= Lifespan of the System,

ν = Inflation Rate,

γ = Loan Interest Rate.

Capacity Q_{BT_CAP} is the design parameter of the battery. Using the capacity of the battery we can calculate the initial cost for the selected energy storage by

$$I_{BT} = \alpha_{BT} Q_{BT_CAP} \qquad \textit{(FORMULA 20)}$$

where

I_{BT}= Initial cost of battery,

α_{BT}= Per-unit cost of the system [USD/Wh],

Q_{BT_CAP}= Capacity of the battery [Wh].

The maintenance cost of the energy storage is calculated by

$$OM_{BT} = \alpha_{OM_{BT}} Q_{BT_CAP} \sum_{j=1}^{N_p} \left(\frac{1+\nu}{1+\gamma}\right)^j \qquad \textit{(FORMULA 21)}$$

where

OM_{BT}= Operation and Maintenance Cost of the Battery,

$\alpha_{OM_{BT}}$ = Yearly per-unit Operation and Maintenance Cost of the Battery [USD/year/Wh],

Q_{BT_CAP} = Capacity of the Battery [Wh],

N_p= Lifespan of the System,

ν = Inflation Rate,

γ = Loan Interest Rate.

Variable $P_{BT}(t)$ represents power that is available from the battery at the time t. This can be determined by

$$P_{BT}(t) = (SOC(t) - SOC_{min}) * Q_{BT_CAP} \qquad \textit{(FORMULA 22)}$$

where

$P_{BT}(t)$ = Available power from the battery at the time t,

$SOC(t)$ = State-of-Charge of the battery at the time t,

SOC_{min} = Minimum SOC,

Q_{BT_CAP} = Capacity of the battery [Wh].

This leads to a multi-objective optimization problem where both unmet energy percentage

$$UME = \frac{\sum_{t=1}^{T} P_d(t) - P_{PV}(t) - P_{WT}(t) - P_{BT}(t)}{E} \qquad \textit{(FORMULA 23)}$$

and overall cost

$$COST = \frac{\sum_{i=PV,WT,BT_{CAP}} (I_i + OM_i)}{N_p} \qquad \textit{(FORMULA 24)}$$

of the energy system are minimized as follows

$$\begin{aligned}
&min_{A_{PV},A_{WT},Q_{BT_CAP}}\ UME + COST \\
&s.t.\ \ 0 \leq A_{PV} \leq u_{PV}, \\
&\qquad 0 \leq A_{WT} \leq u_{WT}, \\
&\qquad 0 \leq Q_{BT_CAP} \leq u_{BT_{CAP}}, \\
&\qquad t \in [0, t_{MAX}], \\
&\qquad P_{PV}(t) = C_{PV}(t) * A_{PV}, \\
&\qquad P_{WT}(t) = C_{WT}(t) * A_{WT}, \\
&\qquad P_{BT}(t) = C_{BT}(t) * Q_{BT_CAP}.
\end{aligned}$$

The optimization has configurable upper bounds for each design parameter (u_{PV}, u_{WT} and u_{BT_CAP}).

Solving the multi-objective directly by a pareto search optimization solver, led to suboptimal results. The following modification of the multi-object optimization problem into an optimization problem

which minimizes the unmet energy (UME) and constraints the cost of the energy system led to better results:

$$min_{A_{PV},A_{WT},P_{BT_CAP}}\ UME = \frac{\sum_{t=1}^{T} P_d(t) - P_{PV}(t) - P_{WT}(t) - P_{BT}(t)}{E}$$

$$s.t.$$

$$\left(\tilde{I}_{PV} + \widetilde{OM}_{PV}\right) * A_{PV} + \left(\tilde{I}_{WT} + \widetilde{OM}_{WT}\right) * A_{WT} + \left(\tilde{I}_{BT} + \widetilde{OM}_{BT}\right) * Q_{BT_CAP} \leq u_{COST},$$

$$0 \leq\ A_{PV} \leq\ u_{PV},$$

$$0 \leq\ A_{WT} \leq\ u_{WT},$$

$$0 \leq\ P_{BT_{CAP}} \leq\ u_{BT_{CAP}},$$

$$t\ \in [0, t_{MAX}],$$

$$P_{PV}(t) = C_{PV}(t) *\ A_{PV},$$

$$P_{WT}(t) = C_{WT}(t) *\ A_{WT},$$

$$P_{BT}(t) = C_{BT}(t) *\ Q_{BT_CAP},$$

where

$\tilde{I}_i := \frac{I_i}{A_i}$, i = $PV, WT,$

$\widetilde{OM}_i := \frac{OM_i}{A_i}$, $i = PV, WT,$

$\tilde{I}_{BT} := \frac{I_{BT}}{Q_{BT_CAP}}$,

$\widetilde{OM}_i := \frac{OM_i}{Q_{BT_CAP}}$.

This modified optimization problem can now be solved multiple times for various fixed upper bounds (u_{COST}) for the cost. Note that the overall cost can also be replaced by yearly cost, since the factor $1/N_p$ can be removed without changing the problem. By this procedure we can solve the original multi-objective optimization problem by multiple runs of a single objective (modified) optimization problem with the addition of the cost as linear constraint.

4 NUMERICAL RESULTS

First part of this chapter explores testing of the various optimization setting in order to find a balance between consistent results and computing time. The second part of the chapter focuses on results that the optimization algorithm produced with the parameters given in tables 4 – 7.

MATLAB's optimization package offers great built-in flexibility through various settings. In the remainder we will use MATLAB's optimization algorithm fmincon with approximated gradients by finite difference method. Since fmincon is a local optimization algorithm, the optimization result is influenced by the choice of the initial point. Using the multi-start fmincon optimization it is possible to run multiple optimization runs from a predefined number of initial points in order to reduce the probability to end up in suboptimal results. Low number of multi-start points offer a faster runtime but with a risk of settling to a non-optimal local minimum influenced by the choice of the initial point. High number offers better results but take significantly longer to compute. Multi-starts of 5, 15 and 25 were ran in order to determine the ideal number of multi-starts for our use case. With low resolution budget that has 12 upper bounds the results don't fluctuate significantly as seen in figure 6. In contrary to higher resolution budget with 32 upper bounds and multi-start of 5, the non-optimal local minimum is clearly visible as a deviation from the pareto front (19) in figure 7. This can be avoided by raising the number of multi-starts in our setting. It was found that 15 multi-start points is a good balance between accuracy and computing time in this configuration.

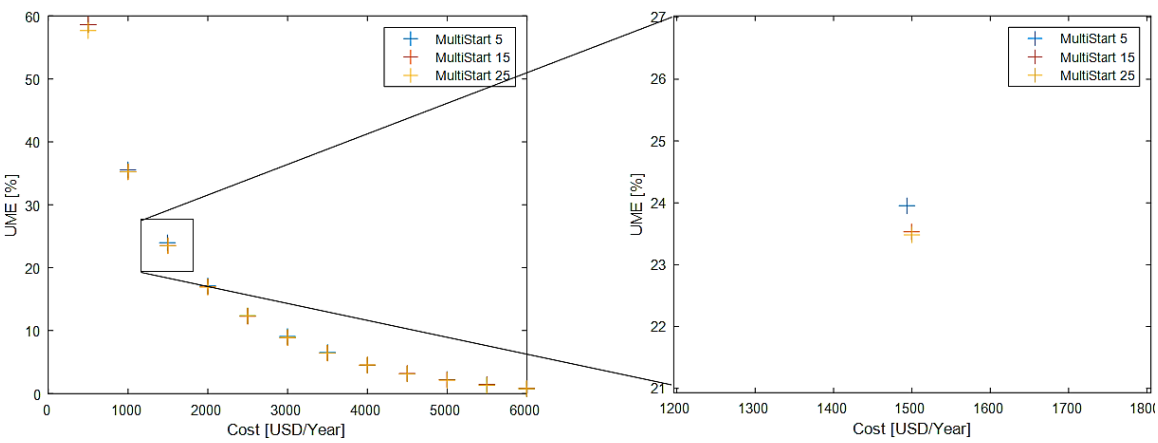

FIGURE 6. Different Multi-start Values

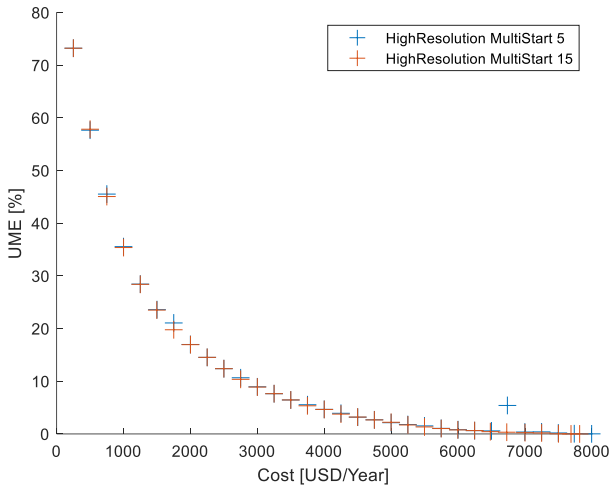

FIGURE 7. High Resolution Multi-start Values

To test the model, a test scenario has to be set. This scenario is defined by weather data, load profile, location and parameters. For this thesis the scenario was chosen to be in north Norway, using the research article "Multiobjective Optimization of a Hybrid Wind/Solar Battery Energy System in the Arctic" by Thanh-Tuan Nguyen and Tobias Boström (6) as a benchmark. The load profile for this simulation is a simplified village load that was defined in subchapter 2.4, and the parameters are listed in tables 4,5,6 and 7.

Table 4. Scenario parameters

Latitude	L	69.4˚N
Local Longitude	LL	19.0˚E
Inflation Rate	ν	9%
Interest Rate	γ	12%

Table 5. Photovoltaic parameters

PV Efficiency at STC	$\eta_{PV_{STC}}$	21%
PV Converters Efficiency	η_{Con}	95%
PV Per-Unit Cost	α_{PV}	350 USD/m²
PV Operation & Maintenance Cost	$\alpha_{OM_{PV}}$	4.3 USD/Year/m²

Table 6. Wind turbine parameters

Specific Power	$P_{specific}$	250 W/m²
Cut-in Wind Speed	v_{ci}	3 m/s
Rated Wind Speed	v_r	10 m/s
Cut-out Wind Speed	v_{co}	22 m/s
Wind Turbine Efficiency	η_{WT}	32.75%
Wind Turbine Converters Efficiency	η_{ConvWT}	95%
Wind Turbine Hub Height	h	90m
Wind Turbine Per-Unit Cost	α_{WT}	384 USD/m²
Wind Turbine Operation & Maintenance Cost	$\alpha_{OM_{WT}}$	2.5 USD/Year/m²

Table 7. Battery parameters

Li-ion Battery Per-Unit Cost	α_{BT}	156 USD/Wh
Li-ion Battery Operation & Maintenance Cost	$\alpha_{OM_{BT}}$	10 USD/Wh

By running the optimization algorithm, it generates the pareto curve visualized in figure 8. The upper bounds for the cost for this numerical study were varied from 2500USD to 60 000USD in 2500USD intervals. From these results it can be concluded that in order to obtain a fully self-sufficient village, the costs are increasingly expensive, but can be achieved with the budget of 60 000USD per year for this specific location. An optimal cost effective result would be to generate around 80% of the local energy demand while keeping the cost below 15000USD per year.

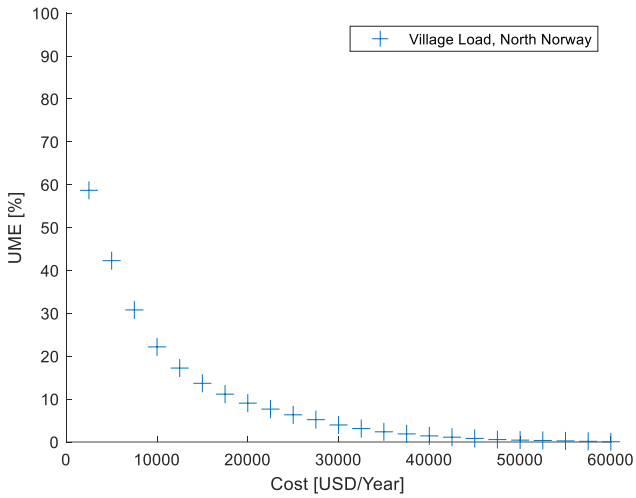

FIGURE 8. Pareto front of the scene with multi-start 15

Figures 9 and 10 tell more about the design parameters at selected cost points. Due to the high availability of local wind energy, the optimization favors this resource. At near full energy self-sufficiency, storage has a key role in supplying power, to the extent that the optimizer decreases power production in order to allocate more budget into increasing the capacity of the storage. This decrease is due to the lack of wind and solar resources (figure 11), instead, the optimization opts to store the energy when energy generation was possible using larger capacity storage.

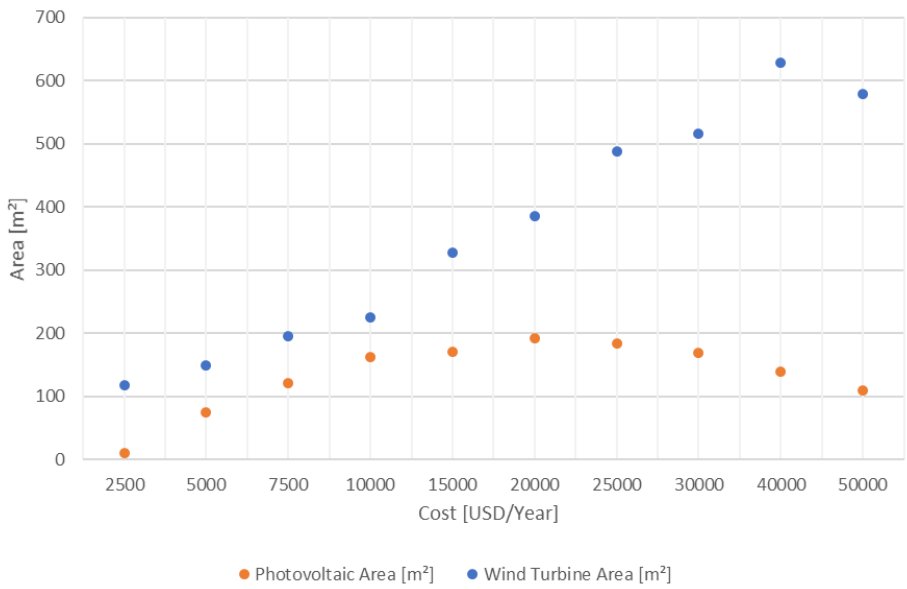

FIGURE 9. PV and Wind Turbine areas at certain budgets

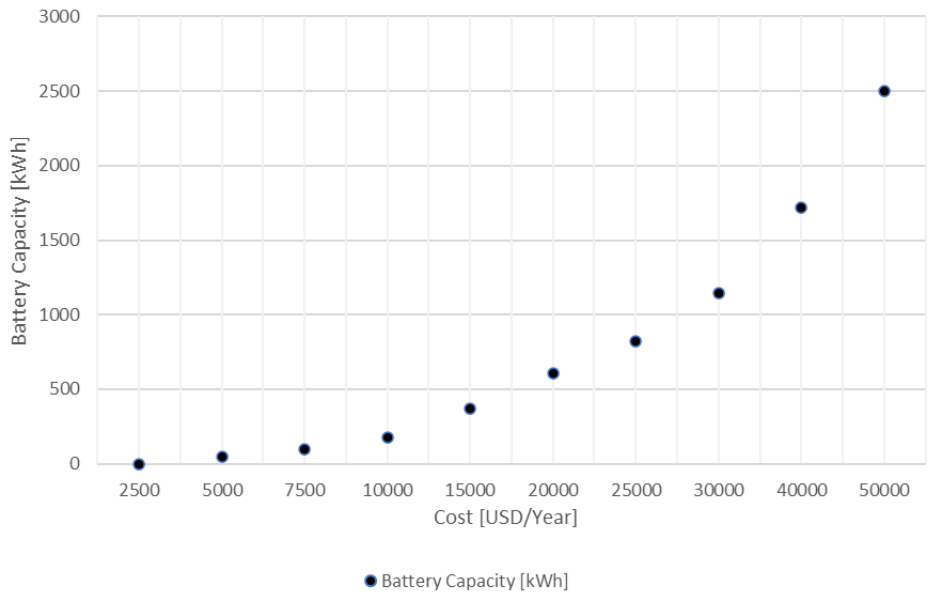

FIGURE 10. Battery Capacity at certain budgets

While using intermitted renewable energy, an energy storage is necessary in order to have a reliable access to electricity at all hours, especially at arctic latitudes where the scenario is situated. This can be seen in figure 11, when there is no possibility to generate energy, it must be supplied from the battery. The figures 11 and 12 are from selected dates with the budget of 40 000USD where only 1.43% of the energy demand was unmet. At this budget the design parameters for PV, WT and BT were 138.34m², 627.95m² and 1716.5kWh. As shown in figure 12, these are the usual situations in which there is unmet energy demand. This occurs when there is not enough wind and solar energy available to meet the demand, and the storage is depleted.

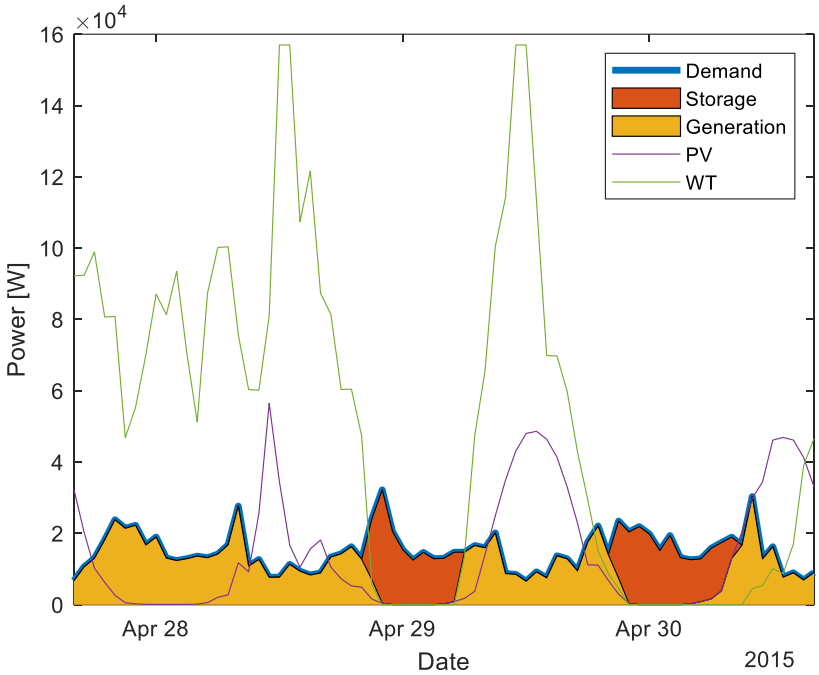

FIGURE 11. Example of the importance of storage

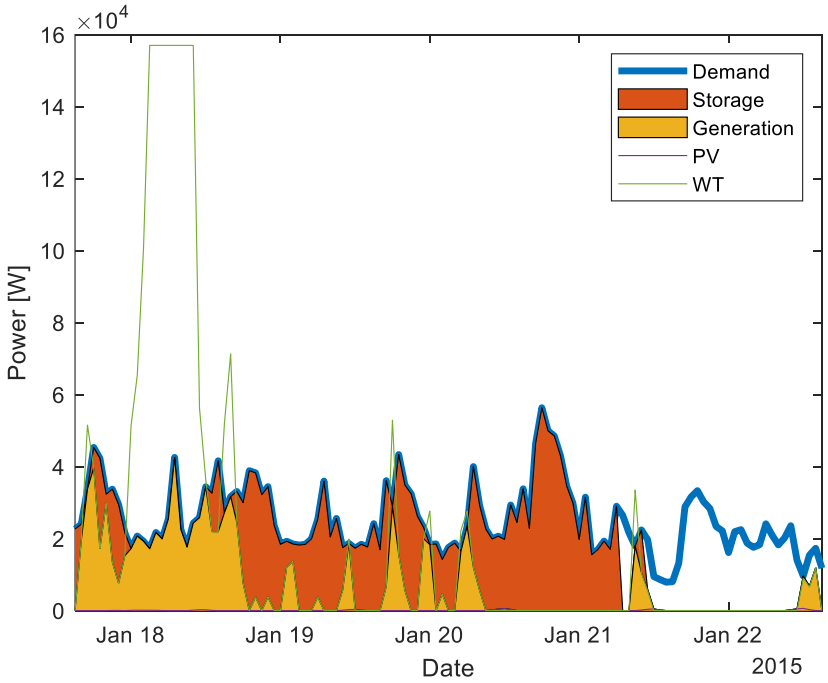

FIGURE 12. Example of depletion of storage

5 CONCLUSION

The aim of this project was to create a simple and flexible simulation model of a green energy system for a village, and to demonstrate that the tools used by the company are capable of optimising the results. Each of the energy systems were coded in MATLAB and Simulink, the code for them is available as appendices. With this model it is possible to get an optimized energy system for a given energy load profile and selected weather data. The flexibility and simplicity of the model allow for modular configuration of the demand and supply components, this enables the model to function as a base for more specialized scenarios.

Results of this thesis highlight the challenge of self-sufficiency with intermitted renewable energy sources and the importance of energy storage system. The numerical outputs of the optimization are a guideline for theoretical energy solutions and with further refinement can become reasonable energy solution for reality.

This project can be further developed to get more accurate results for more complex situations. By choosing different weather dataset or load profile, the results of the optimization are completely different. The versatility of the model allows the change of the scene to be straightforward.

The next steps for this project are to model an energy source capable of covering baseload, for example, grid connection or bio-gas power plant. Increasing the complexity of the systems with static parameters in order to be more accurate. Demand can be made more realistic by constructing a load profile generator or using some existing tools for this.

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APPENDICES

The appendices show how each systems formulas were implemented as MATLAB code inside Simulink function blocks and an overview of the Simulink model.

```
function PVPower = my_Solar(AirTempC, SunGlobInc, Globalpar, PVArea)


%% Calculate eff. with Cell temperature, and Cell temperature with irradiance and
ambient temperature


Tcell = -999;
if AirTempC <= 200   %% if under 200, then Tambient
    Tcell = AirTempC;


elseif (200 <= SunGlobInc) && (SunGlobInc <= 400)   %% if over 200 but under 400,
then Tambient + 5C
    Tcell = AirTempC + 5;


elseif (400 <= SunGlobInc) && (SunGlobInc <= 600)   %% if over 400 but under 600,
then Tambient + 10C
    Tcell = AirTempC + 10;


else %% if over 600, then Tambient + 20C
    Tcell = AirTempC + 20;
end


if Tcell == -999
    disp('Error: Temperature of the PV cell is not calculated.');
end


EffPV = Globalpar.PVEffSTC-(Globalpar.PVTempCoeff*(Tcell - 25)); %% Calculate
temperature impacted eff. with eff. PV standart test condition eff. and
Temperature(here 25C).


%% Calculate PV power.


PVPower = SunGlobInc .* PVArea .* EffPV .* Globalpar.PVEffConv; %% Get PV power
with the Formula
end
```

```
function [WTPower,WTstate]= my_Windturbine(Windspeed, AirTempC, WTArea, Globalpar)


WTPnom = Globalpar.WTspecificP * WTArea; %% Windturbine nominal power in W
AirTempK = AirTempC + 273.15; %% airtemperature from Celsius to Kelvin
AirDensity = Globalpar.AirPressure./(Globalpar.Rpecific*AirTempK); % Calculate air
density


%% Initial states
WTPower = 0;
WTstate = 0;


%% Windturbine operation, When windspeed is lower than minimun = no power, when
windspeed is at the rated window = generate the rated amount of power, when
windspeed is between minimum and rated = generate proportional power


if (or(Windspeed <= Globalpar.Windspeed.CutIn,Windspeed >=
Globalpar.Windspeed.CutOut))
    WTPower = 0;
    WTstate = 0;
elseif or((Globalpar.Windspeed.Rated <= Windspeed) && (Windspeed <=
Globalpar.Windspeed.CutOut),(0.5 * AirDensity .* Windspeed.^3 .* WTArea *
Globalpar.WTEff * Globalpar.WTEffConv)>=WTPnom)
    WTPower = WTPnom;
    WTstate = 2;
elseif (Globalpar.Windspeed.CutIn <= Windspeed) && (Windspeed <=
Globalpar.Windspeed.Rated)
    WTPower = 0.5 * AirDensity .* Windspeed.^3 .* WTArea * Globalpar.WTEff *
Globalpar.WTEffConv;
    WTstate = 1;
else
    disp('error')
end


end
```

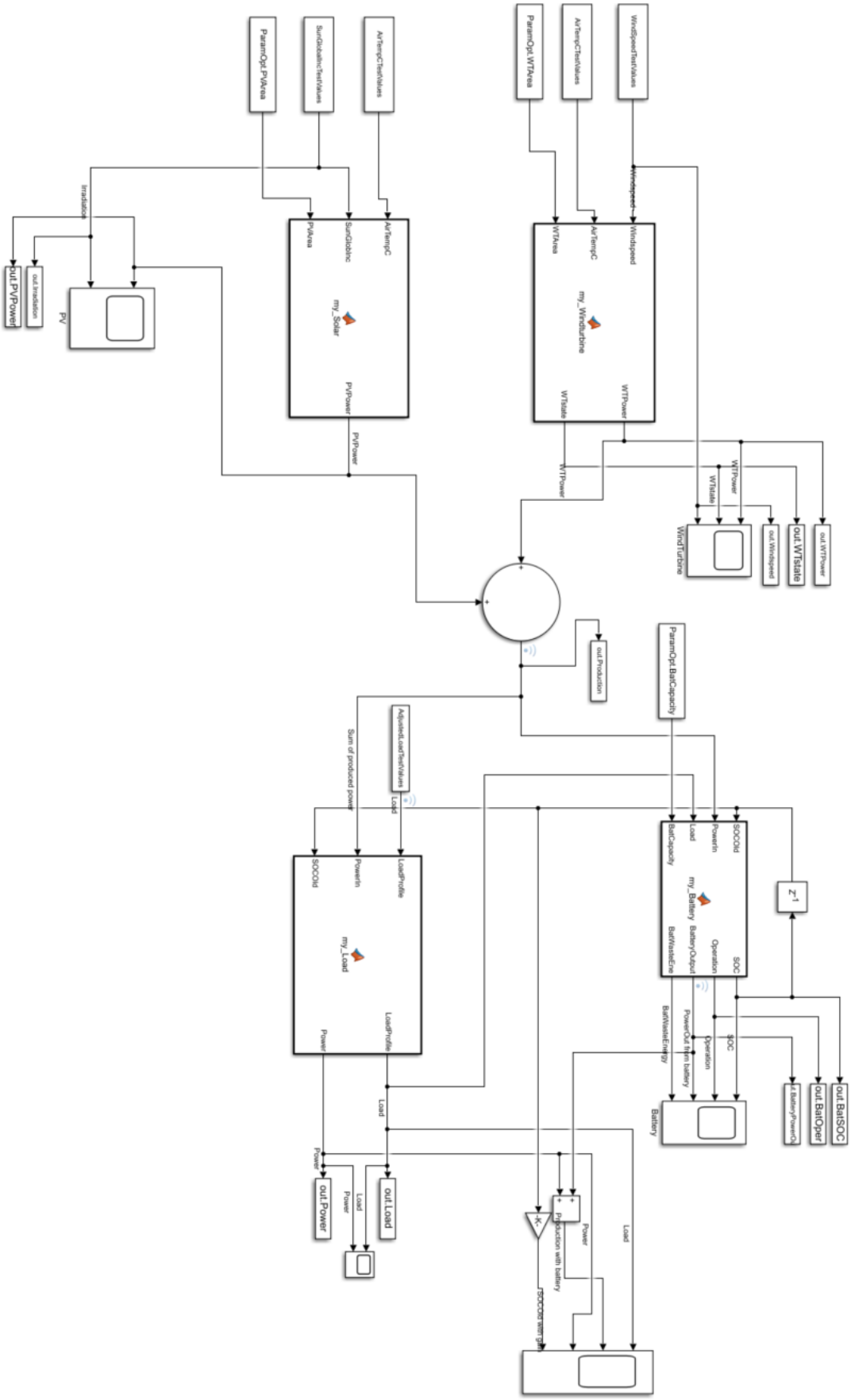
```
function [SOC, Operation, BatteryOutput, BatWasteEne] = my_Battery(SOCOld,
PowerIn,Load, BatCapacity)


DOD = 0.8; %% Depth of Discharge %
SOCmin = 1-DOD;
SOCmax = 1; %% Set limits for SOC
Operation = -1; %% Set initial Operation
BatteryOutput = 0; % initial condition for power out
% % Operation, 0 = Stand-by, 1 = Discharging, 2 = Charging, 3 = excess
% production
BatWasteEne = 0;
dP = PowerIn - Load; %% Difference of production and load, positive = excess of
production


%% Trim SOC
SOC = SOCOld + (dP/BatCapacity);
if SOC >= SOCmax
    BatWasteEne = (SOC - SOCmax) * BatCapacity;
    SOC = SOCmax;
    Operation = 3;
elseif SOC <= SOCmin
    SOC = SOCmin;
    Operation = 0;
end


%% Battery operation.
if (dP <= 0) && (SOC > SOCmin)
    BatteryOutput = (SOCOld - SOC) * BatCapacity;
    Operation = 1;
elseif (dP > 0) && (SOC < SOCmax)
    Operation = 2;
end


% Operation not set should not happen
assert(Operation >= 0)
end
```

Simulink model overview.

APPENDIX 4/4