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***Abstract*—Fifth-generation energy networks are combined networks of heat and electricity, that have the ability to generate, distribute, store and share energy between consumers. Knowledge on the dynamic behaviour of the physical phenomena related to energy generation, distribution and storage provides insight into the performance of the system as a whole. A mixed-integer linear algorithm is proposed, implementing a partitioned clustering program for subsequent classification of typical demand, grouping specific days with similar demand profiles together. From this arrangement, the optimal network configuration can be determined using an objective function, minimizing the economic and environmental impact. To validate the optimization results, a simulation of the network was built, which mimics its physical dynamic behaviour, and through which the distribution and storage capabilities of the network can be assessed. Advanced advice on fifth-generation energy networks is presented that can be applied to early-stage network design, reducing costs and emissions, along with data on the implementation of renewable energy technologies and their performance. Additionally, this research provides the foundation for numerical modelling of such energy networks which contributes to future research.**

***Index Terms*—Community Energy Storage, Fifth-generation Energy Systems, Thermal Energy Storage**

I. Introduction

To reach the targets set by the Paris Climate-agreement, the European Union (EU) must make efforts to improve the current district energy networks. Fifth-generation energy networks are combined networks of heat and electricity, that have the ability to generate, distribute, store and share energy between consumers, as shown in Figure 1. These networks depend heavily on renewable sources and sustainable technologies, when their designs are optimized for cost and CO_2 reduction. To overcome the challenges of meeting the demand for heating and cooling, different approaches are considered at the district heating level, such as scheduling multiple boilers with thermal energy storage systems (TESS) [1], [2], coupling TESS of different volumes into the heat distribution system [3], reducing the power curtailment of wind power through combined heat and power (CHP) units and store the energy into TESS [4], and creating multi-energy systems with distributed energy sources and energy storage systems throughout the network [5], [6].

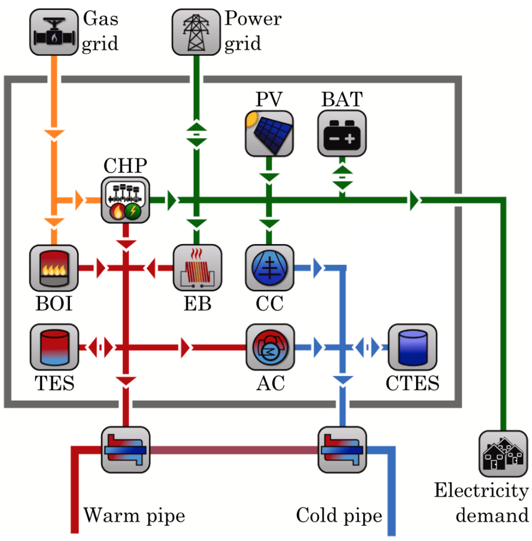


Fig. 1: Structure of the fifth-generation energy network, the gas boiler (BOI), the CHP unit and the electric boiler (EB) are used to generate heat. The compression chiller (CC) generates cold. Electricity is generated by photovoltaic thermal (PVT) modules. Operational flexibility is increased by the implementation of a TES, cold storage (CTES) and a battery (BAT) [7].

After the literature review [1]–[7], it was found that most of the research uses fixed size TESS, instead of studying the effect of the sizing of the TESS on the resulting network. The contribution of the present work is, therefore, to provide insight about the impact of the optimal sizing of thermal

Thanks to SWECO for providing the data for the case scenario.

energy storage systems at the district heating network level. This optimization is achieved through a method based on mixed integer linear programming (MILP), combined with a clustering algorithm, which minimizes the CO_2 emissions and the economic costs related with the volume of the TESS. This information can be used towards understanding the dynamic behaviour of the physical phenomena related to energy generation, distribution and storage provide as a whole.

This work is divided as follows: Section II presents a detailed explanation on the optimization algorithm used to minimize either the total annualized costs (TAC) or the CO_2 emissions. Then, a case study, using a district heat demand profile provided by SWECO, is used in Section III to validate the optimal sizing of the TESS volume, as result of the optimization algorithm. The behaviour of a fifth-generation energy network, using a Simulink model, is also presented to demonstrate the influence of a TESS within the energy network. Those results are, then, discussed in Section IV highlighting their importance, and Section V concludes the research, providing recommendations on further research, based on this work.

II. Optimization Algorithm

In this research, the costs and emissions related to the operation of a TESS within fifth-generation energy network are quantified. In order to optimize this network, a mixed integer linear algorithm is used to size the volume of a thermal energy storage system, implementing a partitional clustering program for subsequent classification of typical demand, thus grouping specific days with similar demand profiles together. From this arrangement of days, associated with a weighting factor ω_d, the optimal network configuration can be determined using the objective function

$$O(\Gamma) = (1-\Gamma)\cdot O_{\mathrm{TAC}} + \Gamma \cdot O_{\mathrm{CO_2}}\,, \tag{1}$$

where $O(\Gamma)$ is the optimization objective, and Γ is the optimization focus, which can range from 0 to 1, where 0 optimizes based only on the TAC, and 1 optimizes based only on the CO_2 emissions of the resulting system. The optimization factors can be obtained as

$$O_{\mathrm{TAC}} = \min \sum_{k\in K} C_\mathrm{i} = 0\,, \tag{2}$$

and

$$O_{\mathrm{CO_2}} = \min \sum_{k\in K} e_\mathrm{i} = 1\,, \tag{3}$$

given

$$O_{TAC} \leq O(\Gamma) \leq O_{\mathrm{CO_2}}\,. \tag{4}$$

As can be seen, the cost function in (1) can be divided in two terms: one related to the economic costs of the system O_{TAC}, and one related to the environmental impact, considered as the CO_2 emissions of the system. The first can be defined as

$$\mathrm{TAC} = C_{\mathrm{EN}} + C_\mathrm{g} + C_\mathrm{e} - R_\mathrm{f}\,, \tag{5}$$

where the energy network cost C_{EN} is a function of the investment I_k, the annual recovery α_k[1] and the operation and maintenance costs f_k per each k technology used in the energy network, given as

$$C_{\mathrm{EN}} = \sum_{k\in K} i_k cap_\mathrm{k}\,(a_\mathrm{k} + f_\mathrm{k})\,, \tag{6}$$

the gas costs C_g, as function of the heat flow generated from the purchased gas for the chiller unit, $\dot{G}_{\mathrm{CHP}}$, and the gas boiler, $\dot{G}_{\mathrm{BOI}}$, the energy supply price $p_\mathrm{g}^{\mathrm{work}}$, the nominal capacity, $\dot{G}_{\mathrm{nom}}$, and the capacity price, $p_\mathrm{g}^{\mathrm{cap}}$, is given as

$$\begin{aligned} C_\mathrm{g} = &\sum_{d\in D} w_d \sum_{t\in T} (\dot{G}_{\mathrm{CHP,d,t}} + \dot{G}_{\mathrm{BOI,d,t}}) p_{\mathrm{g,d,t}}^{\mathrm{work}} \Delta t \\ &+ \dot{G}_{\mathrm{nom}} p_\mathrm{g}^{\mathrm{cap}}\,. \end{aligned} \tag{7}$$

Comparably, the electricity costs C_e are

$$C_\mathrm{e} = \sum_{d\in D} w_\mathrm{d} \sum_{t\in T} P_{\mathrm{grid,d,t}} p_{\mathrm{e,d,t}}^{\mathrm{work}} \Delta t + P_{\mathrm{nom}} p_\mathrm{e}^{\mathrm{cap}}\,, \tag{8}$$

as function of the power needed to supply the energy demand, P_{grid}, energy supply costs, $p_\mathrm{e}^{\mathrm{work}}$, grid power capacity, P_{nom} and the capacity costs, $p_\mathrm{e}^{\mathrm{cap}}$. Finally the feed-in profits R_f, as function of the supply power P and the specific feed-in profits r, are

$$\begin{aligned} R_\mathrm{f} = &\sum_{d\in D} w_\mathrm{d} \sum_{t\in T} (P_{\mathrm{f,PVT,d,t}} r_{\mathrm{f,PVT,d,t}}) \Delta t \\ &+ \sum_{d\in D} w_\mathrm{d} \sum_{t\in T} (P_{\mathrm{f,CHP,d,t}} r_{\mathrm{f,PVT,d,t}}) \Delta t\,. \end{aligned} \tag{9}$$

The environmental term of the cost function (1), on the other hand, is defined as

$$e_\mathrm{t} = \frac{e_\mathrm{g} G_\mathrm{T} + e_\mathrm{e}(W_\mathrm{T} - W_\mathrm{f})}{Q_\mathrm{h} + Q_\mathrm{c}}\,, \tag{10}$$

as function of the emissions for burning gas e_g and use electricity from the grid e_e, the total amount of gas used G_T, the total electric power demand W_T, the available feed-in power W_f, and the total energy flow rate from the cold and hot storage units, Q_h and Q_c respectively.

To optimize the energy network, the methodology used is based on MILP. The method applied in this work classifies typical days from multiple intermittent annual demand distributions, considering time steps of Δt = 1h [7]. The numerical model that will be provided here is based on the application of a partitional clustering method known as the k-medoids method [8]. The results are provided for an optimization comprised of clustered data and for a reiteration, where the optimal energy network characteristics are obtained from consist gathered inputs, only the process is optimized. The process is illustrated in Figure 2.

The method starts with the definition of a measure of distance, which quantifies how the demand days differ from each other. The days of the year are grouped into k clusters depending on their demand similarities (distances), which chooses the most centrally located day (medoid) of each

[1] In this work, the investment I_k was assumed as the product of a constant specific investment i_k and the rated power output cap_k per each k technology of the system.

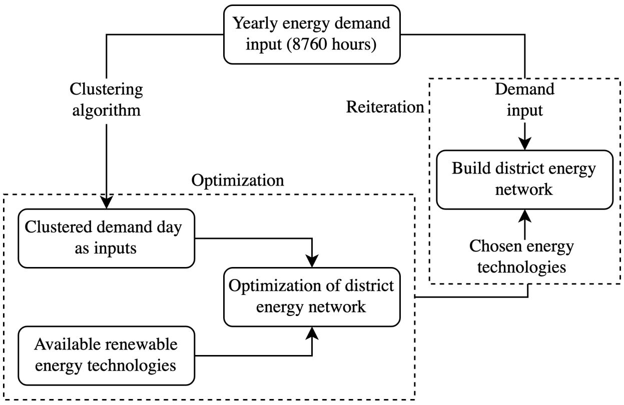


Fig. 2: Optimization and reiteration progression scheme.

cluster as the most typical member [9], [10]. Thereafter, peak demand days are superimposed as insulated clusters. Although all of the data is clustered, important data from the original set is preserved, for instance the load duration curves, the peak demands and the temporal demand distribution. The temporal coincidence can have major effects on the optimum design since demands are always intermittent. The purpose of the model is to combine comparable days (objects) into groups (clusters), so that all of the days in the same group are similar to each other. Thus, different groups will be dissimilar from each other. The implementation of this concept requires two actions: calculating the dissimilarity matrix and implementing a clustering algorithm. For the optimization of an energy network, the medoids' values are scaled to maintain the annual heating, cooling and electricity demands.

The input data used for this model are the annual hourly demands for heating, cooling and electricity. This data set can be formed into a $m \times n$ matrix, with $m = 365$, corresponding to the objects, and $n = 72$, corresponding to the characteristics of the objects, in other words, the hourly loads. In the case of all three scenarios, $1 \leq n \leq 24$ will consist of heating demands, $25 \leq n \leq 48$ of cooling demands and $49 \leq n \leq 72$ for the electricity demands.

In order to define the distance d between two days, that is, the calculation of the dissimilarity between objects i and j, the equation for the Minkowski distance

$$d(i,j) = \left(\sum_{\mathrm{k}=1}^{72} |a_{\mathrm{i,k}} - a_{\mathrm{j,k}}|^p \right)^{\frac{1}{p}} \tag{11}$$

can be applied, where p is order of the Minkowski distance [11]. For the instance that $p = 2$, 1 or ∞ the equation returns the Euclidean-, Manhattan and maximum distance respectively. The characteristics in this matrix should be normalized, but first checked for deviations prior to applying (11). The distances between the objects can be organized into a symmetric matrix named the dissimilarity matrix $\boldsymbol{D}$.

To ensure that peak days are always selected, the k-medoids algorithm chooses k real days as representative days. This does, however, not guarantee that the annual demands are preserved, since the daily demands which belong to the same cluster differ from the demand of the representative day of the cluster. To make sure to maintain the total annual demand, correction factors are given to the representative days (not counting peak days). For each i, where i - 1,2,...,n, such that y_i = 1. As described by [8], there are three scaling coefficients applied and calculated as follows

$$\text{Heating:} \quad \omega_i^h = \frac{\sum_{\mathrm{j}=1}^{n} z_{\mathrm{i,j}} \sum_{\mathrm{g}=1}^{24} a_{\mathrm{j,g}}}{nc_i \sum_{\mathrm{g}=1}^{24} a_{\mathrm{j,g}}}, \tag{12}$$

$$\text{Cooling:} \quad \omega_{\mathrm{i}}^{\mathrm{c}} = \frac{\sum_{\mathrm{j}=1}^{\mathrm{n}} z_{\mathrm{i,j}} \sum_{\mathrm{g}=25}^{48} a_{\mathrm{j,g}}}{nc_{\mathrm{i}} \sum_{\mathrm{g}=25}^{48} a_{\mathrm{j,g}}}, \tag{13}$$

$$\text{Electricity:} \quad \omega_{\mathrm{i}}^{\mathrm{e}} = \frac{\sum_{\mathrm{j}=1}^{\mathrm{n}} z_{\mathrm{i,j}} \sum_{\mathrm{g}=49}^{72} a_{\mathrm{j,g}}}{nc_{\mathrm{i}} \sum_{\mathrm{g}=49}^{72} a_{\mathrm{j,g}}}. \tag{14}$$

where nc_{i} is the number of days in cluster C_{i}, which includes the medoid.

III. RESULTS

The optimization algorithm was tested using demand data from a case study, provided by the company SWECO, as detailed in Section III-A. This is a still to be constructed, renewable residential area that uses mostly renewable heat from a solar thermal park. This research will focus on the heat generation from a solar thermal park that supplies the residential heat demand. Energy demands for the case study are measured to provide approximately 10.000 households with heat. In this case study, the neighborhood is assigned an area of roughly 55 000 m^2, that can be filled with solar thermal collectors (STC), photovoltaics (PV) or a combination of both (PVT). Furthermore, the behaviour of the network was demonstrated by constructing a multi-domain simulation of a fifth-generation energy network on Simulink, as presented in Section III-B, using the optimal tank results found in the previous Section.

A. Optimization of the Tank Volume

The case study is assumed to have a maximum available area of 55 000 m^2, occupied by photovoltaic thermal collectors, with an efficiency of 40% thermal, and 15% electrical. The variable optimization objective is implemented in Python, using Gurobi, with the values shown in Tables I, II and IV, to minimize either overall costs or CO_2 emissions, or a combination of both, as detailed in Section II. Three different scenarios have been modelled that supply: 1) a heating demand, 2) a heating and cooling demand, and 3) a heating, cooling and electricity demand. The heating, cooling and electricity demands are shown in Figure 3. It was found that an optimal balance between costs and CO_2 emissions is obtained at an optimization objective of $\Gamma = 0.5$. At that point, the size of the thermal buffer for the aforementioned scenarios are: 1) 1819 m^3, 2) 1975 m^3 and 3) 1100 m^3. Likewise, the overall costs and CO_2 emissions show to have: 1) 31.9% and 28.8%, 2) 10.5% and 47.8%, and 3) 23.9% and

TABLE I: Economic parameters for energy generation and storage technologies

	PVT	STC	BOI	CHP	EB	CC	TES	BAT
i [€/a]	1250	400	150	1000	80	600	500	500
t_L [year]	20	20	20	15	22	15	20	10
a_{inv} [%]	9.00	9.00	8.02	9.87	7.75	9.87	8.02	12.95
f_k [%[a]]	1.0	2.0	3.0	8.0	1.0	3.5	2.0	1.0

[a]Percentage of the total investment.

TABLE II: Gas and electricity prices

p_g^{cap} [k€/kW]	p_g^{work} [€/kW]	p_e^{cap} [k€/kW]
12.15	28.24	59.66

TABLE III: Electricity supply costs and feed-in profits [€/MWh]

	p_{el}^{work}	$r_{feed\text{-}in,PVT}$	$r_{feed\text{-}in,CHP}$
Minimum	28.14	-21.34	-49.66
Maximum	207.85	152.46	127.38
Average	139.79	85.03	60.08

TABLE IV: Environmental parameters, e.g. the specific CO_2 emissions (e) and the primary energy factor (PEF)

CO_2 emissions	Natural gas	Electricity from grid
e [kg/MWh]	201	516

14.9% less than the reference scenario of a traditional network.

In order to give a clearer view on the result of changing the optimization focus, O, the entire model is iterated from 0 to 1. Here, 0 is a minimization in the TAC and 1 is a minimization of the CO_2 emissions. Cover the entire heat demand with just heat generated by PVT system is difficult, thus, heat pumps are used to provide the remainder of the demand. This is done mostly during winter where there is less sun and more heat demand. Note that, in theory, a TESS can be designed big enough to cover the heat demand during winter also, however, this will not necessary be an optimal usage of resources in terms of costs or environmental impact, reason why the optimal results are crucial within a proper design of the whole network. The optimal size of the TES is dependent on the demand and the generation of heat from the PVT system. Figures 4a, 4b and 4b provide the values for the optimal volume and the amount of charging cycles of the TES unit as function of the optimization focus O for each scenario. Figure 4a presents results for scenario 1. It can be seen that the size of the storage volume reaches a peak. The turning point shows that the amount of charging cycles is of great importance to the size of the TES. Likewise, Figure 4b depicts the optimal TES volume for scenario 2 and shows a rapid increase in volume until around 2000 m^3 at $O = 0.45$, after which it remains relatively constant. The charging cycles increase strongly at this point, which is likely due to the increase of power generated by the PVT modules. In both cases, the charging cycles also remain between 180 and 200 cycles. Finally, Figure 4c yields results for scenario 3. Interestingly, the size of the TES unit seems to be reduced in volume with an increasing optimization focus. This result provides information on the amount of CO_2 emissions, it becomes apparent that increasing the volume costs more CO_2 emissions than if a comparable amount of energy is taken from the grid, for example, to drive heat pumps. When this happens, the thermal load is transferred to the electrical load, therefore relieving the TESS.

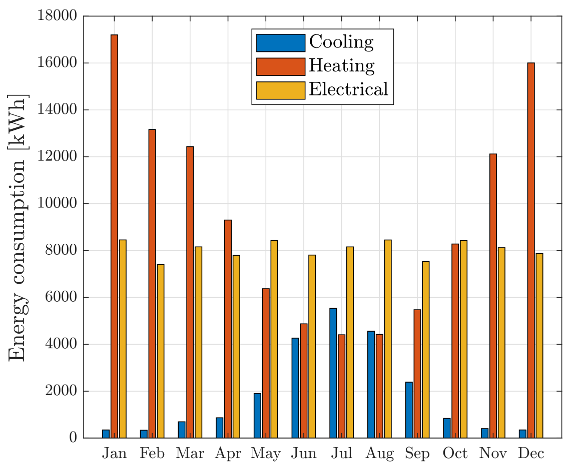


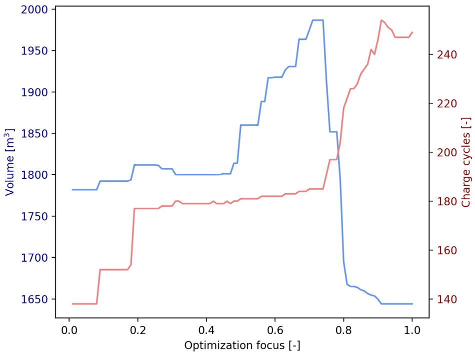
Fig. 3: Monthly energy demand of the municipality for the case study.

B. Behaviour of the Thermal Energy Storage System

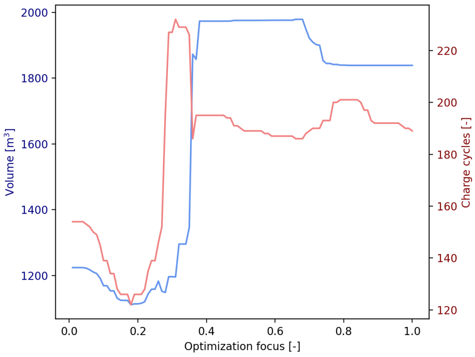
To demonstrate the effects of the TESS on the system, a photovoltaic thermal modules system, coupled with a daily thermal buffer system of 2 000 m^3, as found in the optimization in Section III-A, and seasonal thermal energy storage, considered as infinite heat source, are simulated. The results shows that the heat demand of the case scenario can be fully satisfied in the period from April until August, as shown in Figure 5. Renewable heat supply shows an average of approximately 7.9 MW, and a maximum of approximately 40.4 MW, during that period. Heat supply shows an approximate temperature of 30-35 °C in winter and 60-65 °C in summer. Electrical power generation from the PV system shows an estimated daily yield of 14 MW. The upper limit of the daily buffer is reached between May until halfway through July, excess heat is transferred to the seasonal storage system, as shown in Figure 6a, and the daily variations can be seen in Figure 6b. The internal daily buffer temperature reaches 20-30 °C during winter and 50-60 °C during summer. Consequently, heat loss of 2-4 kW in winter and 8-12 kW is found.

IV. Discussion

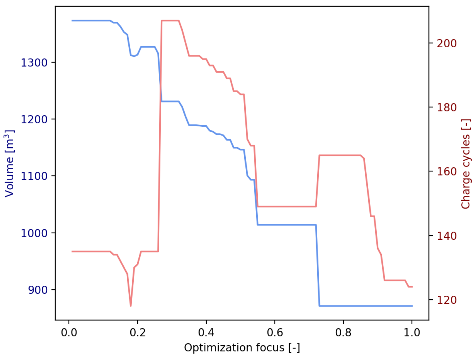
For the three cases, the results demonstrate that the balance point of the minimization of economic costs and CO_2 emissions is near $O = 0.5$. At this point, the volume of the TES



(a) Scenario 1.



(b) Scenario 2.



(c) Scenario 3.

Fig. 4: Optimal volume and charging cycles for each scenario as function of the optimization focus O and a constant thermal efficiency $\eta = 0.5$

reaches a maximum value, keeping constant and then dropping dramatically. This can be explained by the fact that the amount of CO_2 emissions associated to increasing the storage volume is larger that the amount of CO_2 emissions related to taken that amount of electricity from the grid. In addition, an increase in capacity arises due to the decrease in volume. An incremental increase in charging cycles are seen as function of increasing thermal efficiency, the volume size follows a overall increase in size.

Each scenario is dependent on a certain energy demand, the initial heat demand for the case study is used in scenario 1. To give an understanding of the amount of costs and emissions saved by implementing renewable energy technologies, a reference scenario has been used that supplies the demand with zero renewable energy technologies. This reference scenario is considered as a traditional network that uses electricity taken from the network and fossil fuels to generate energy. Table V gives the total annualized costs, total CO_2 emissions, share of renewable and electricity/gas taken from the grid for an optimal network opposed to the reference scenario (traditional network). All three scenarios depict a steep increase of renewable energy technologies from a optimization focus of $O = 0.25$, after which is stays relatively constant. For an increasing module efficiency there is a linear increase in renewables.

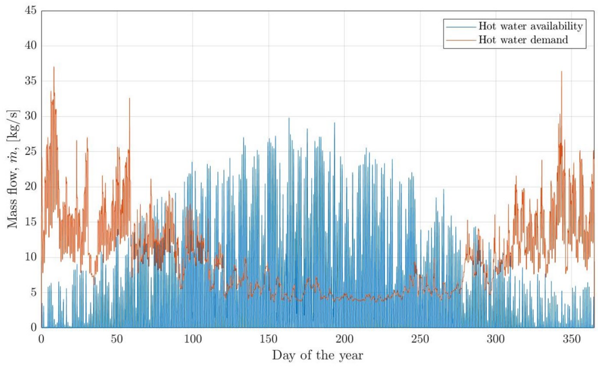
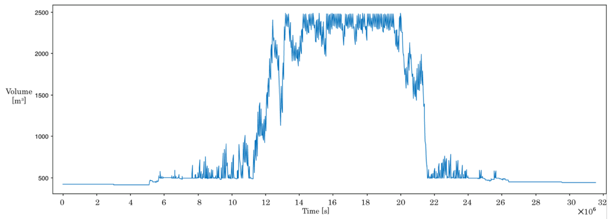
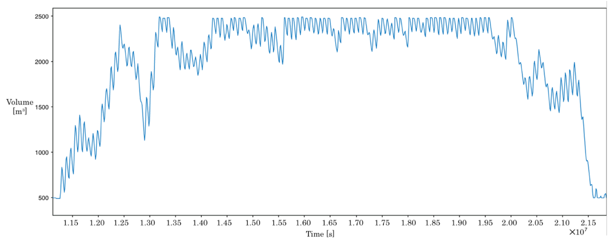


Fig. 5: Heat demand of the community, and availability from the PVT system.



(a) Volume of the daily buffer throughout the year.



(b) Volume of the daily buffer during summer.

Fig. 6: Volume of the daily buffer.

TABLE V: Results for the optimal energy network for each scenario, compared to the reference scenario.

	Scenario 1	Scenario 2	Scenario 3
Total annualized costs €/a	-31.9%	-10.5%	-23.9%
Total CO_2 emissions [tonnes/a]	-28.8%	-47.8%	-14.9%
Share of renewables	58.7%	32.1%	6.6%
Electricity/gas demand [MWh]	-64.4%	-72.3%	-46.0%

The effect of solar variability on renewable energy generation and storage still requires a traditional heat generation facility. Depending on the amount of solar irradiation, energy is produced and used to satisfy a demand. This research assumes the environment for the north of the Netherlands as location solar energy generation. The variability between winter and summer is so large that the supply will never be able to provide the demand fully during winter.

The intermittent behaviour of the solar variables creates an alternating heat supply. In general, the heat demand is larger than the supply. However, when the heat supply exceeds the demand (often during summer), any excess heat is stored in the daily storage buffer. The dynamic behaviour of the daily storage buffer for the continuous measurement depict an overall increase in volume and temperature. When the volume increases, fluctuations in the temperature decrease which stabilize heat loss. When the supply exceeds the demand, and thus increases the buffer volume, the temperature of the buffer will increase relative to the temperature input and the volume of the buffer. Eventually, and equilibrium will be reached that stabilizes the amount of heat loss. Note that the behaviour of the daily TES is roughly constant during the summer season, as the energy acquired during the day is, either used immediately, or stored for later use during the night. The slight changes shown in Figure 6b can be interpreted as the fact that the TES is working at it maximum capacity, therefore, the energy exchange (*i.e.* both the energy extracted and returned) with external sources is minimized, whereas during winter, most of the heat is external, as the heat availability is low, when compared with the head demand.

V. Conclusions

This research provides a technological approach to the optimization, distribution, and dynamization of a fifth-generation energy network with detailed information on its optimal configuration, energy dissipation and dynamic behaviour. It was demonstrated that increasing the size of the tank does not ensure a cost reduction, nor a decrease in the CO_2 emissions. Instead, an optimal point has to be found, which must be considered during the early stages of fifth-generation energy networks design, in order to reduce its costs and emissions. What is more, results on the implementation of renewable energy technologies and their performance were provided, showing the seasonal effect of the TESS on the network. Additionally, this research provides the foundation for numerical modelling of such energy networks, which contributes to future research. The most important recommendations considered for further research, based on this work:

1) Varying the amount of input parameters to acquire a greater sensitivity for results. For example: investment costs (C_i), life time (LT), O&M costs (OM), electricity price (C_e), and CO_2 tax (t_{CO2}).
2) Applying this model to a electrical network only with the implementation of a electrical battery, to determine optimal configuration and benefit of electrical batteries within a fifth-generation energy network.
3) Instead of using a fixed maximum available area, extend the boundary condition of this value to see the impact on the implementation of renewable energy generation technologies. This method can be applied to a certain energy demand with an unknown area, leading to a feasibility study for that certain demand.
4) Further simulation with an advanced piping network can increase the understanding of a more realistic behaviour of heat flow through a fifth-generation energy network.
5) Consider a traditional heat source in the model to balance the additional demands, and simulate the seasonal buffer as an aquifer buffer.
6) Add a real-time electrical power demand to investigate the behaviour of the photovoltaic panels.
7) Include electrical storage to enhance the variability of the network to supply an electrical power demand.

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