2018 Building Performance Modeling Conference and
SimBuild co-organized by ASHRAE and IBPSA-USA
Chicago, IL
September 26-28, 2018

SENSITIVITY OF LOW-VOLTAGE GRID IMPACT INDICATORS TO WEATHER CONDITIONS IN RESIDENTIAL DISTRICT ENERGY MODELING

Christina Protopapadaki[1,2], Dirk Saelens[1,2]
[1]KU Leuven, Department of Civil Engineering, Building Physics Section, Heverlee, Belgium
[2]EnergyVille, Genk, Belgium
contact: christina.protopapadaki@kuleuven.be

ABSTRACT

Heat pumps and photovoltaic systems become more common in residential neighborhoods, where they alter the traditional relationship with the electricity distribution grid, causing congestion and voltage problems. This paper investigates the influence of weather data on low-voltage grid impact indicators calculated within a previously developed probabilistic framework. We compared results for seven different synthetic weather years, generated for Belgium using Meteonorm, ranging from “average” to “extreme cold winter and sunny summer”, as well as two future scenarios for 2050. Since peak demand and generation are influenced by ambient temperature and solar irradiation respectively, extreme values in weather inputs can potentially determine the outcome of an impact analysis. We, therefore, argue not to rely on average synthetic weather year profiles. Additionally, the impact of using a single representative week as alternative to year-long simulation was investigated.

INTRODUCTION

Residential heat pumps (HP) and photovoltaic systems (PV) have seen rapid market growth the past years in Europe and North America, due to regulations and incentives aiming to reduce energy consumption and CO_2 emissions (European Commission 2016). These technologies can significantly impact electricity load patterns, with influence not only at the system level (Quiggin and Buswell 2016; Love et al. 2017), but also at the local distribution grid (Navarro-Espinosa and Ochoa 2016; Haque and Wolfs 2016; McKenna et al. 2018). Technical constraints at the distribution grid level may limit the potential penetration of such technologies in practice, as this would require load control, specialized equipment, storage or grid reinforcement, at considerable cost (Baetens 2015; Haque and Wolfs 2016). As a result, more and more research is devoted to studying their impact on the low-voltage (LV) distribution grid.

In previous work, we have developed a probabilistic framework for grid impact assessment, which combines detailed Modelica simulations with a Monte Carlo approach varying neighborhood-level parameters (Protopapadaki and Saelens 2017a). Such complex approaches require a series of assumptions and simplifications which introduce uncertainty in the result. In (Protopapadaki and Saelens 2017b), the influence of several modeling assumptions and boundary conditions has been investigated for this framework. The analysis provided insight into the accuracy loss resulting from low resolution data and grid simplifications, while also highlighted the necessity to consider uncertain global parameters, such as the reference secondary voltage at the distribution transformer.

To complement previous efforts, this paper examines the significance of weather inputs in such grid impact analyses. Weather conditions not only influence the heating demand, but also the generation of renewable energy, such as solar or wind energy. Furthermore, air-source heat pumps consume more when the ambient temperature is low, not only because of reduced efficiency, but also due to activation of auxiliary electric resistance heating elements. As peak values and simultaneity of loads are the main drivers of grid overloading, the influence of different weather profiles needs to be evaluated. At the same time, it is important to determine whether shorter simulation periods allow capturing these important effects, and if so, how they can be defined.

The impact of weather, and in particular of climate change, on building energy use has been widely researched (de Wilde and Coley 2012). Generation of synthetic weather profiles for sensitivity and uncertainty analysis in building simulation is a topic of growing interest (Rastogi 2016; Goffart, Mara, and Wurtz 2017). Though sector-level analyses have been performed to estimate weather impact on electricity demand (Li, Yang, and Lam 2012; Santamouris et al. 2015), implications on the grid infrastructure have received little attention (Heinen et al. 2017). Furthermore, grid impact analyses are performed for specific or *typical* years (McKenna et al. 2018), or only for few *critical* days (Navarro-Espinosa and Ochoa 2016).

This paper investigates the sensitivity of grid impact indicators to the choice of weather data and simulation period. The indicators, namely voltage and load levels, are determined based on annual simulations for a variety of scenarios, generated within a probabilistic framework we previously developed (Protopapadaki and Saelens 2017a). While this framework uses data for Belgian grids, a similar approach could be used for the same analysis in other countries. Note that we focus on the choice of weather data for a given location, and not on varying climatic zones. More specifically, comparisons are made for indicators resulting from different synthetic weather year data, generated by Meteonorm 7.1. Advanced settings allow to produce more variable data series with monthly or annual maxima/minima for temperature and irradiation. We have compared 7 different weather years ranging from "average" to "extreme cold winter and sunny summer", as well as two future scenarios for 2050. Additionally, we examine whether a specific week can be selected to represent the behavior of the entire year.

METHODOLOGY

The sensitivity study is performed based on a probabilistic simulation framework described in previous work (Protopapadaki and Saelens 2017a). The next section provides a short summary of the framework and simulation models, followed by a description of the grid impact indicators. Then, the various weather profiles used for the analysis are presented.

Probabilistic framework and simulation models

A Monte Carlo approach is employed to simulate two residential distribution islands for a variety of pre-simulated household loads and generation profiles, for different weather conditions. Simulations of buildings with heat pumps, of the PV generation and the network are carried out in Dymola, using the Modelica `IDEAS` library, while stochastic occupant behavior is included from the `StROBe` package of `openIDEAS` (Baetens et al. 2015; Baetens and Saelens 2016; Jorissen et al. 2018). This approach allows for detailed models of thermal systems, capturing their dynamic behavior in high resolution to provide input for the electrical simulations.

In particular, 100 buildings with heat pump are created, based on sampling of their geometric and thermal properties from predefined parameter distributions for the Belgian stock. Three variants are made to represent detached, semi-detached and terraced dwellings. Two-zone detailed building models are automatically generated in the Dymola environment on basis of the sampled parameters. All buildings are equipped with an individually sized air-source heat pump that provides for both space heating via radiators and domestic hot water. The heat pump COP is dependent on operating conditions, and a unity power factor is assumed for the load. Emission system and water storage tank are also explicitly modeled. Each building is assigned stochastic occupant profiles determining space heating set-point, hot water requirements, internal heat gains and electricity consumption for plug-loads and

Table 1: Grid parameters.

	Description	Values
T	Neighborhood type	rural, urban
Q	Construction quality	new, renovated, old
Ca	Cable strength	weak, strong *
T_{kVA}	Transf. rated capacity, kVA	160, 250, 400
U_{ref}	Reference transf. voltage, pu ‡	U (0.95,1.05)
HP	HP penetration rate per feeder, %	U (0,100)†
PV	PV penetration rate per feeder, %	U (0,100)

* Cable cross-section area depends on feeder size per case.
† U (a,b) denotes a uniform distribution between a and b.
‡ pu (per-unit): voltage as fraction of nominal voltage (230 V).

Table 2: Main grid impact indicators.

	Description
U_{min}	Minimum annual 10-min voltage §, pu
$U_{min}^{95\%w}$	Minimum of all weekly voltage 5th percentiles, pu
P_{t+}	Transformer peak real power demand, kW
P_{t-}	Transformer peak back-feeding, kW

§ 10-min average line-to-neutral RMS voltage, at last connection of each phase.

lighting. An optional rooftop PV system is further defined, which consists of a pre-simulated generation profile, adjusted and scaled to the orientation and size of each particular building's system. PVs are single-phase connected to the grid, and are therefore limited to 5 kWp. Belgian distribution network operators currently do not accept single phase inverters above 5 kVA (Synergrid 2012).

The considered networks consist of a rural and an urban distribution island, as shown in Figure 1. The distribution transformers supply 64 and 85 residential consumers through 4 and 5 radial feeders respectively, representing *typical* Belgian LV grids (Baetens 2015). These are three-phase, four-wire, wye systems, with nominal voltage of 230/400 V at 50 Hz. The `IDEAS` library provides models for three-phase unbalanced power flow analysis of LV grids using a quasi-stationary method and assuming constant frequency (Van Roy, Salenbien, and Driesen 2014).

The feeders supply neighborhoods with varying degrees of heat pump and PV penetration rates (percentage of buildings with the system), and buildings of diverse heating needs. The various grid parameters and their respective values, derived for Belgian LV grids, are summarized in Table 1. A maximin Latin Hypercube Sampling scheme is used to create 5 permutations of 180 samples of the mentioned parameters in Table 1 (Husslage et al. 2011). To account for variability in buildings and their location on the network, 5 replications of each design point are produced. For each replication, buildings with heat pumps and optional PV are sampled from the previously generated set and assigned to random locations on the grid. When no heat pump is present, only the base-load electricity consumption profile is assigned to that building.

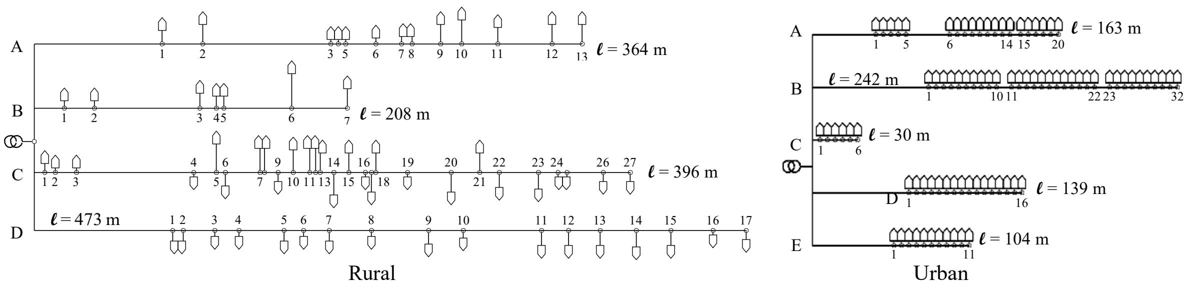

Figure 1: Distribution islands representing typical Belgian rural and urban grids, according to Baetens (2015).

Table 3: Weather scenarios with their temperature and irradiation settings, generated by Meteonorm 7.1.

Label	Description	Temperature	Irradiation
1-Avg	Average year,starting seed=1	Average	Average
2-1-AvgSeed5	Average year, starting seed=5	Average	Average
2-2-AvgSeed10	Average year, starting seed=10	Average	Average
3-AvgTempExtr	Average year with extreme temperature variations	Average (10 year extreme hour variation)	Average
4-Cold	Cold year	Yearly minima	Average
5-Sunny	Sunny year	Average	Yearly maxima
6-CoW-SunS	Extreme cold winter and sunny summer	Monthly minima in winter, average in summer	Monthly maxima in summer, average in winter
7-2050Avg	2050 average year	Average	Average
8-2050CoW-SunS	2050 extreme cold winter, sunny summer	Same as 6	Same as 6

Grid impact indicators

Table 2 summarizes the indicators used in the present analysis. These variables are selected to examine voltage violations per feeder, and transformer loading for entire distribution islands. Voltage level limitations are prescribed in Europe by EN 50160 (2000), which requires the 10-min averaged root mean square (RMS) voltage to remain within ±10 % of the nominal ($U_n = 230\ V$) for 95 % of time each week, and between +10 % and -15 % U_n for all time. The upper limit is not further examined in this paper, as it is only exceeded for up to 0.35 % of the feeders in the worst weather scenario, and only for cases with reference transformer voltage U_{ref} close to 1.05 pu.

Concerning transformer loading, which is a thermal problem, the 30-min averaged peak load is evaluated, both for demand and back-feeding. Annual energy demand and local production are important as well, but the effect of weather on those has already been analyzed in literature.

Weather scenarios

Various types of *typical weather years* have been developed and used in building simulations. Rastogi (2016) offers an overview of those, as well as a review of synthetic weather generators. Meteonorm is a commercial software that provides such synthetic typical weather data for various locations (Remund et al. 2015). This software focuses on solar radiation and temperature, which influence heat pump loads and PV generation the most. Additionally, it offers options to produce more extreme and variable weather conditions, as well as future climate change scenarios. As such, it was selected for the generation of annual weather profiles for this analysis.

More specifically, 9 weather profiles were created, two of which represent future scenarios in 2050. All profiles were generated for Uccle, a weather station in the center of Belgium, often taken as reference in country-level studies. For all non future profiles, we used historical data from periods 1991–2010 for radiation, and 2000–2009 for temperature. Other advanced settings were kept the same for all profiles, for instance the starting seed (except scenarios 2) and the various radiation models.

Scenarios 1 and 2 are average years, with average monthly irradiation and temperature, and average hourly temperature extremes (standard option). Scenarios 2-1 and 2-2 are created to investigate the impact of different first random seeds. scenario 3 differs from scenario 1 in the temperature model, which uses 10-year hourly extremes. The mean monthly temperature remains the same in both cases. To simulate rare climatic events, a cold year is generated, who's mean annual temperature has a probability of happening once in a decade (scenario 4). Similarly, a sunny year has mean irradiation exceeded only once in 10 years (scenario 5). For extreme rare events, scenario 6 combines an extremely cold winter with an extremely sunny summer, which will both increase heating loads in the winter and PV production in the summer. In this year, each winter month has its lowest mean temperature for a decade, while each summer month has its highest

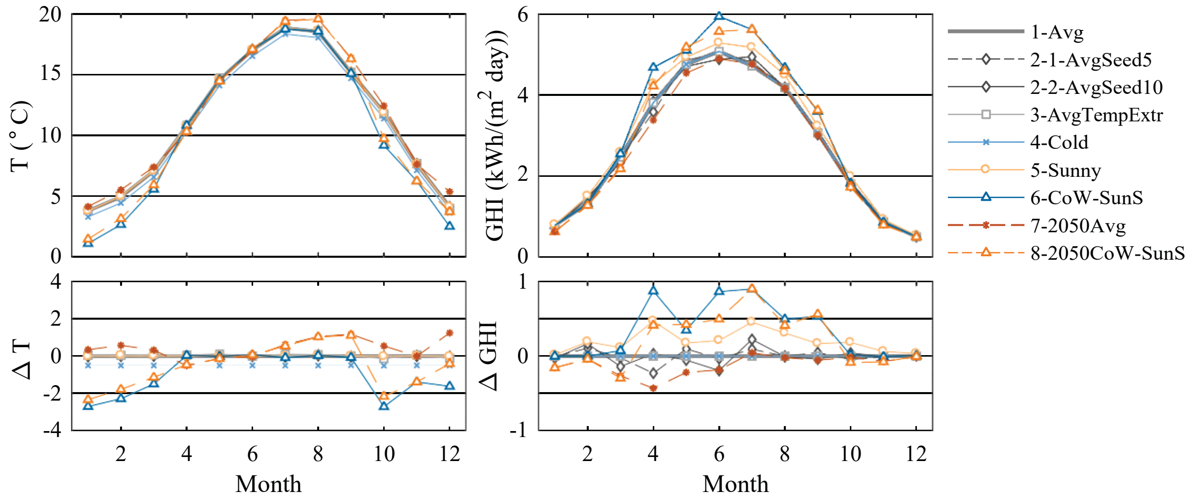

Figure 2: Top: Monthly mean ambient temperature and global horizontal irradiation for all scenarios. Bottom: difference compared to scenario 1-Avg.

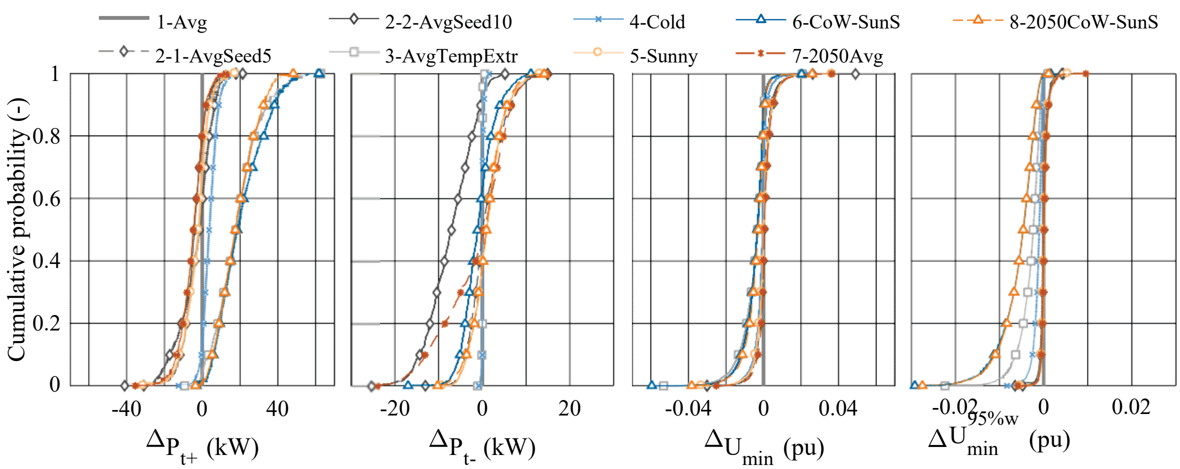

Figure 3: Empirical cumulative distribution function of the change in indicators (Table 2) compared to scenario 1-Avg.

mean irradiation for a decade. Such year combines extreme scenarios for every month, making it improbable to occur as a whole. Future scenarios 7 and 8 are equivalent to scenarios 1 and 6, but for 2050. Among three options for future projections, the A1B IPCC scenario was chosen, because it showed larger deviations from scenario 1 in annual mean temperature and irradiation, but also in monthly means—warmer winter and less sunny summer. Table 3 gives an overview of all scenarios and Figure 2 shows the monthly mean temperature and irradiation.

RESULTS

Impact of weather scenario

Figure 3 shows the distribution of change in the four main indicators induced by different weather scenarios, compared to the first scenario. Overall, extreme scenarios 6 and 8, where the winter is colder on average (see Figure 2), generate the larger deviations, both in terms of peak demand and voltage levels. This is expected, given that monthly temperature minima were selected for those scenarios. Similar effect can be observed for scenario 3, even though only the daily extreme temperatures were different. This indicates a large dependence of the annual peak load and voltage on temperature, and consequently, on heat pumps and their back-up electric elements. For $U_{min}^{95\%w}$, the impact of daily extremes is smaller, as values below the weekly 5th percentile are not considered. A colder on average year, scenario 4, also reduces voltage levels, but in a more uniform way, mainly influencing $U_{min}^{95\%w}$.
Interestingly, for non-extreme scenarios, feeders are equally likely to have positive or negative changes in voltage compared to scenario 1, regardless of their parameters (Table 1). This highlights how sensitive these indicators are to the random coincidence of loads. While

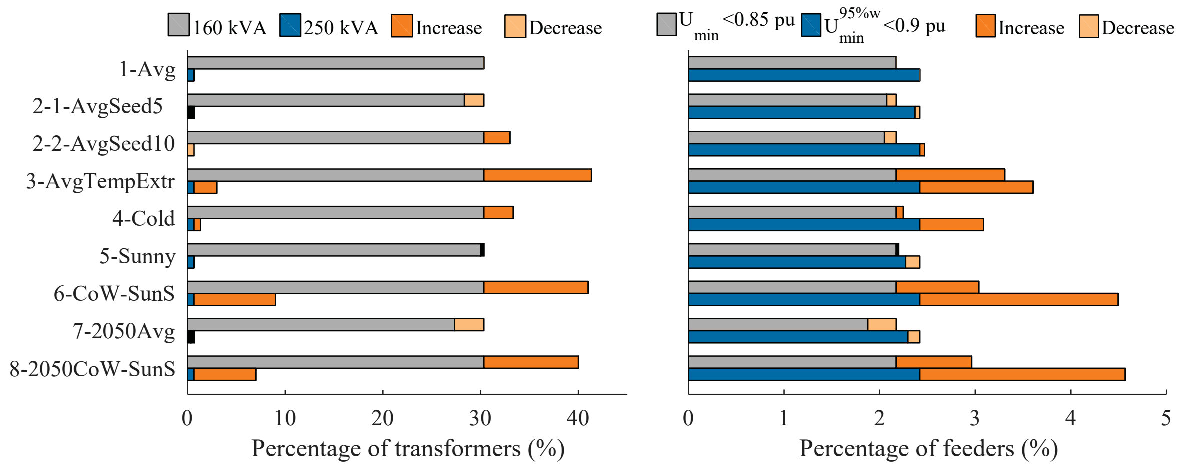

Figure 4: Left: Percentage of transformers with absolute peak loads over rated capacity, per transformer size. Right: Percentage of feeders with voltage violations. Bar colors show the 'increase' or 'decrease' compared to scenario 1-Avg.

the base electricity loads remain practically the same for all weather scenarios, small shifts in temperature cause different peaks in heating demand, and can so alter the voltage profiles. Another instance where randomness has significant impact can be seen in the large increase in (negative) back-feeding transformer peak load P_{t-} for scenarios 2-2 and 7. Even though mean irradiation is maintained at similar levels as for scenario 1 (see Figure 2), a single extreme irradiation peak combined with a low-demand weekday caused P_{t-} to increase for many transformers.

With regard to climate change, future scenarios 7 and 8 have overall higher mean temperatures and less irradiation than their reference scenarios 1 and 6 (Figure 2). Peak demand and voltages are mostly positively influenced, while deviations in back-feeding peak are mainly driven by random peaks in irradiation, as already explained.

While Figure 3 showed the absolute change in indicators due to different weather profiles, the bar charts in Figure 4 demonstrate the influence on conclusions drawn from an impact analysis. The percentage of transformers with overloading problems and the feeders with voltage issues are shown. Notably, about 30 % of the smaller transformers (160 kVA) are overloaded; that is when important shares of heat pumps are introduced in their networks. This percentage increases importantly if a year with extreme temperatures is simulated, such as for scenarios 3, 6 and 8. In these cases, also 250 kVA transformers start having problems. For somewhat colder (scenario 4) or warmer (scenario 7) weather, violations increase and decrease, respectively, but to a lesser extent. For non-extreme weather scenarios (2-1, 2-2 and 5), changes—not always insignificant—can only be attributed to randomness.

Overall, weather conditions have an important effect on grid impact analyses. Using an average weather year profile with average temperature variations will underestimate potential problems in the grid, for networks with highly electrified space heating. It is, therefore, advisable to additionally employ weather profiles that capture temperature extremes.

Representative period

As simulation time become important in probabilistic analyses, it is valuable to investigate the possibility of reducing the simulation period for grid impact analyses. Obviously, this relates to peak indicators, and could not be valid for estimation of annual energy exchange, for instance. Based on the results of annual simulations for all weather scenarios, we examine whether a week can be seen as *representative*. The same analysis can be performed for smaller periods, e.g. for a single day, but this is not presented here, as it doesn't allow quantification of $U_{min}^{95\%w}$. In any case, it is assumed that loads are pre-simulated or measured for each period, free of initialization issues.

Three criteria are used to select the most *representative* week for all four indicators of Table 2. These require calculating those indicators for all simulated cases and for each given week, and compare that to the values obtained from the entire annual data series. A sliding window of seven days with step of one day is used, providing 359 options for choosing the best week. In this paper, weeks are selected independently per indicator, to assess whether there are differences.

The first criterion is the Root Mean Square Error (RMSE):

$$RMSE(j) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{i,year} - x_{i,j})^2} \qquad (1)$$

where n is the amount of simulated feeders (n=4050) or islands (n=900), $x_{i,j}$ is the value of indicator x for case i, calculated based on week j, and $x_{i,year}$ is the value calculated based on the entire year. Best week is the one

Table 4: Resulting selected representative week W (start day) for all indicators, weather scenarios and criteria. The ratio of cases falling in chosen week W_{r_c} is also given (r_c). For definitions, see Equations 1 to 3.

	U_{min}				$U_{min}^{95\%w}$				P_{t+}				P_{t-}			
	W_{RMSE}	W_ρ	W_{r_c}	r_c	W_{RMSE}	W_ρ	W_{r_c}	r_c	W_{RMSE}	W_ρ	W_{r_c}	r_c	W_{RMSE}	W_ρ	W_{r_c}	r_c
1-Avg	11	11	11	.51	10	10	10	.35	9	9	9	.75	130	130	129	.44
2-1-AvgSeed5	11	11	10	.58	10	10	10	.58	9	9	9	.84	139	139	139	.46
2-2-AvgSeed10	11	11	11	.54	10	10	10	.36	11	11	11	.81	194	194	194	.93
3-AvgTempExtr	11	11	10	.47	355	355	355	.37	6	6	6	.51	130	130	135	.44
4-Cold	9	9	11	.52	9	9	9	.57	9	9	9	.75	130	130	129	.42
5-Sunny	11	10	12	.60	10	10	10	.59	11	10	10	.86	139	117	136	.36
6-CoW-SunS	10	10	9	.60	10	10	9	.58	9	9	9	.79	195	146	195	.33
7-2050Avg	11	11	11	.62	10	10	10	.48	9	9	9	.83	145	145	145	.61
8-2050CoW-SunS	10	10	10	.68	10	10	10	.42	9	9	9	.85	157	157	155	.47

that minimizes the RMSE, that is, gives closer results to the annual simulations, for the entirety of simulated cases. The RMSE is chosen as error measure, as it penalizes more extreme deviations.

Second criterion is the Pearson's correlation coefficient:

$$\rho(\mathbf{X}_{year}, \mathbf{X}_j)(j) = \frac{\mathrm{cov}(\mathbf{X}_{year}, \mathbf{X}_j)}{\sigma_{\mathbf{X}_{year}} \sigma_{\mathbf{X}_j}} \quad (2)$$

where $\mathbf{X}_{year}$ is a vector of indicator x for all simulated cases based on annual results, and $\mathbf{X}_j$ is the same, but based on results of week j. cov is the covariance, and σ the standard deviation. ρ takes values between 0 and 1, 1 denoting a perfect linear correlation, meaning that week j perfectly captures the results from annual simulations. The best week is the one with highest ρ.

Last option is selecting the week in which the annual indicator was found for most simulated cases. This is reduced to maximizing the following ratio:

$$r_c(j) = \frac{\sum_{i=1}^{n} [x_{i,year} = x_{i,j}]}{n} \quad (3)$$

where the numerator denotes conditional summation of cases if their indicator in period j is equal to the annual one. For an explanation of symbols, see Equation 1.

Table 4 summarizes the chosen week (start day of the week) for the various scenarios, indicators and criteria. For voltages and peak demand the three criteria seem to agree in most cases, with a deviation of one or two days. This allows identifying a week when the minimum voltage is reached for a majority of feeders (around 50 to 70 %), and the transformer peak demand is found for 50 to 85 % of cases. While for $U_{min}^{95\%w}$ r_c appears to be smaller, this is only because $U_{min}^{95\%w}$ is calculated on a weekly basis itself, so r_c only counts feeders with $U_{min}^{95\%w}$ in the exact same week. Taking into account feeders with $U_{min}^{95\%w}$ also found in weeks one day before and after the selected week would raise these values to 0.5 for scenario 3, around 0.8 for scenarios 1, 2-2 and 4, and above 0.9 for the rest. We additionally observe low r_c values for all three indicators in scenario 3, which is because two different weeks have similarly low temperatures, creating two competing peaks of r_c. This is also the reason why different weeks are selected for the three indicators, while for other scenarios voltage and peak demand clearly coincide.

Figure 5 shows an example of best week selection for U_{min} and scenario 1. The three criteria are shown, as well as the mean and minimum temperature of the same weeks. RMSE is normalized to the unit interval (nRMSE) for this figure.In this example, the chosen week starting on day 11 optimizes all criteria. At the same time, the selected week has the lowest mean and average temperature of the year, which is also the case for all other weather scenarios. This points out once more that temperature dominates heat pump induced voltage problems. We may note, nevertheless, that about 20 % of cases have their minimum voltage around day 355 instead, when temperature is almost as low. Matters of load simultaneity may cause the voltage in those feeders to drop lower then. But, as the correlation and error are optimal in week 11, we can assume for most of those feeders voltage will drop close to their annual minimum in that period as well. One could, therefore, argue that using the coldest week of the year for grid impact analyses with presence of heat pumps, would yield good estimates.

To better assess the impact of selecting one week on voltage violation results, Figure 6 presents the change in percentage of feeders with violations. With regard to $U_{min}^{95\%w}$ the decrease is very limited. However, violation of the lower limit is more sensitive, with underestimation of up to 0.59 percentage points for scenario 3 and below 1.35 for the rest. While these differences might be somewhat significant, they are still smaller than those caused by more extreme weather scenarios. Therefore, with regard to peak load and voltage, computation effort should better be invested into simulating multiple weather conditions for a week, rather than a single annual simulation.

For the peak back-feeding load P_{t-}, the three criteria also generally agree. However, the correlation coefficient ρ is very high for most days of the summer, which makes it less appropriate for selecting a specific week. Indeed,

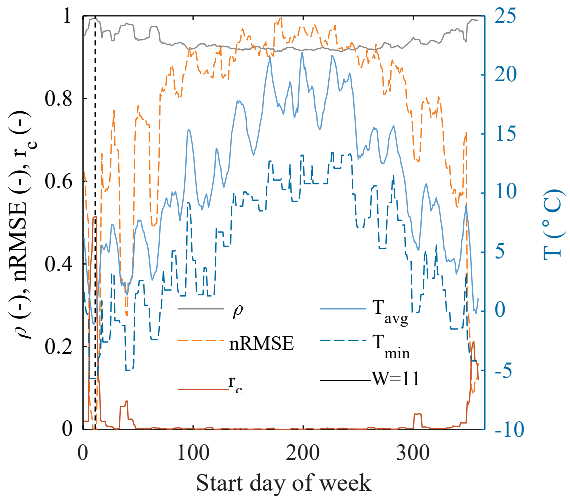

Figure 5: Selection of representative week W for U_{min} and scenario 1-Avg. Left y-axis: Correlation coefficient ρ, normalized RMSE and ratio of feeders with annual U_{min} falling within given week r_c. Right y-axis: Weekly mean T_{avg} and minimum T_{min} ambient temperature.

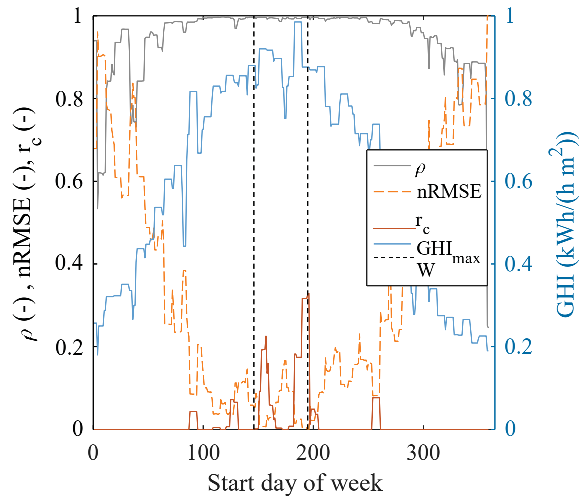

Figure 7: Selection of representative week W for P_{t-} and scenario 6-CoW-SunS. Left y-axis: Correlation coefficient ρ, normalized RMSE and ratio of transformers with annual P_{t-} falling within given week r_c. Right y-axis: Maximum hourly irradiation GHI_{max} per week.

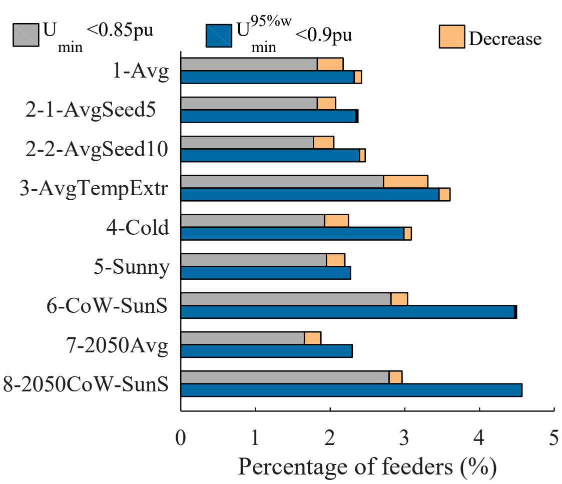

Figure 6: Percentage of feeders with voltage violations for one week simulation (chosen based on RMSE). Bar colors show the 'decrease' compared to annual results.

for scenarios 5 and 6, the latter illustrated on Figure 7, ρ has selected a much different week than the other criteria. While *RMSE* and r_c may have a clear optimum, the chosen week need not necessarily reflect the peaks for a majority of cases, see r_c in Table 4. More importantly, weeks of maximum irradiation do not automatically coincide with the one selected by the indicators, as seen for example in Figure 7. The reason is that, while PV generation is maximized, self consumption may reduce the peak back-feeding power at the transformer. As PV capacity is limited in the examined scenarios to 5 KWp single-phase connection, the stochastic electricity household demand becomes important, especially in cases with low PV penetration rates. Consequently, a specific week cannot be chosen as representative for back-feeding overload based solely on examination of the weather file. The same would be valid in the analysis of over-voltage problems, also caused by peaks in generation. A period of high irradiation peaks could be combined with many random demand profiles to investigate these issues.

CONCLUSION

District energy simulations can be used to evaluate the grid impact of space heating electrification with heat pumps, and PV generation in residential neighborhoods. This paper investigated the influence of an important boundary condition in such simulations, namely the choice of weather data.

Comparison of voltage and load indicators for a range of weather scenarios has shown that relying on an average weather year profile with average temperature variations will underestimate potential problems in the grid. This results from the strong correlation of air-source heat pump loads with the ambient temperature. It is, therefore, advisable to additionally employ weather profiles that capture temperature extremes.

Furthermore, based on the present analyses, it is demonstrated that choosing the coldest week of the year for simulation would yield estimates of voltage issues and peak demand close to the annual simulations. This is the case for networks with important presence of heat pumps. Such approach would save computation effort, to be better spent on different weather scenarios. Nevertheless, in terms of peak back-feeding power, a specific week could not be chosen based solely on examination of the weather file, at least not for the cases analyzed in this paper. Evidently, annual analyses are necessary for other indicators aiming to examine, for instance, overall energy exchange with the electricity grid or self consumption.

ACKNOWLEDGMENT

This work is part of the SBO project S009617N "NEPBC", which receives funding from the Research Foundation - Flanders (FWO).

REFERENCES

Baetens, R. 2015. "On externalities of heat pump based low-energy dwellings at the low-voltage distribution grid." Ph.D. diss., KU Leuven.

Baetens, R., R. De Coninck, F. Jorissen, D. Picard, L. Helsen, and D. Saelens. 2015. "OpenIDEAS an open framework for integrated district energy simulations." *14th Building Simulation Conference*. Hyderabad, 347–354.

Baetens, R., and D. Saelens. 2016. "Modelling uncertainty in district energy simulations by stochastic residential occupant behaviour." *Journal of Building Performance Simulation* 9 (4): 431–447.

de Wilde, P., and D. Coley. 2012. "The implications of a changing climate for buildings." *Building and Environment* 55:1–7.

EN 50160. 2000. Voltage characteristics of electricity supplied by public distribution systems.

European Commission. 2016, November 30. Communication on "Clean Energy For All Europeans".

Goffart, J., T. Mara, and E. Wurtz. 2017. "Generation of stochastic weather data for uncertainty and sensitivity analysis of a low-energy building." *Journal of Building Physics* 41 (1): 41–57.

Haque, M., and P. Wolfs. 2016. "A review of high PV penetrations in LV distribution networks: Present status, impacts and mitigation measures." *Renewable and Sustainable Energy Reviews* 62:1195–1208.

Heinen, S., W. Turner, L. Cradden, F. McDermott, and M. O'Malley. 2017. "Electrification of residential space heating considering coincidental weather events and building thermal inertia: A system-wide planning analysis." *Energy* 127:136–154.

Husslage, B., G. Rennen, E. R. van Dam, and D. den Hertog. 2011. "Space-filling Latin hypercube designs for computer experiments." *Optimization and Engineering* 12 (4): 611–630.

Jorissen, F., G. Reynders, R. Baetens, D. Picard, D. Saelens, and L. Helsen. 2018. "Implementation and Verification of the IDEAS Building Energy Simulation Library." *Journal of Building Performance Simulation*. Published on line.

Li, D. H.W., L. Yang, and J. C. Lam. 2012. "Impact of climate change on energy use in the built environment in different climate zones - A review." *Energy* 42 (1): 103–112.

Love, J., Andrew Z.P. Smith, S. Watson, E. Oikonomou, A. Summerfield, C. Gleeson, P. Biddulph, L. Chiu, J. Wingfield, C. Martin, A. Stone, and R. Lowe. 2017. "The addition of heat pump electricity load profiles to GB electricity demand: Evidence from a heat pump field trial." *Applied Energy* 204:332–342.

McKenna, R., P. Djapic, J. Weinand, W. Fichtner, and G. Strbac. 2018. "Assessing the implications of socioeconomic diversity for low carbon technology uptake in electrical distribution networks." *Applied Energy* 210:856–869.

Navarro-Espinosa, A., and L. F. Ochoa. 2016. "Probabilistic impact assessment of low carbon technologies in LV distribution systems." *IEEE Transactions on Power Systems* 31 (3): 2192–2203.

Protopapadaki, C., and D. Saelens. 2017a. "Heat pump and PV impact on residential low-voltage distribution grids as a function of building and district properties." *Applied Energy* 192:268–281.

Protopapadaki, C., and D. Saelens. 2017b. "Sensitivity of low-voltage grid impact indicators to modeling assumptions and boundary conditions in residential district energy modeling." *15th Building Simulation Conference*. San Francisco, 752–760.

Quiggin, D., and R. Buswell. 2016. "The implications of heat electrification on national electrical supply-demand balance under published 2050 energy scenarios." *Energy* 98:253–270.

Rastogi, P. 2016. "On the sensitivity of buildings to climate : the interaction of weather and building envelopes in determining future building energy consumption." Ph.D. diss., EPFL.

Remund, J., S. Müller, S. Kunz, B. Huguenin-Landl, C. Studer, D. Klauser, C. Schilter, and R. Lehnherr. 2015. Meteonorm Handbook Part I: Software.

Santamouris, M., C. Cartalis, A. Synnefa, and D. Kolokotsa. 2015. "On the impact of urban heat island and global warming on the power demand and electricity consumption of buildingsA review." *Energy and Buildings* 98:119–124.

Synergrid. 2012. Technical specifications on connection requirements for generators to distribution grid C10/11 (in French and Dutch).

Van Roy, J., R. Salenbien, and J. Driesen. 2014. "Modelica library for building and low-voltage electrical AC and DC grid modeling." *10th International Modelica Conference*. 301–309.