THE EFFECT OF HOURLY PRIMARY ENERGY FACTORS ON OPTIMAL NET-ZERO ENERGY BUILDING DESIGN

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ABSTRACT

This paper demonstrates how primary energy factors (PEFs) affect the quantification of site versus source energy use in buildings. Present best practice involves the application of a single annual scaling factor. This approach is insufficient for electrical grids where a portfolio of generation technologies exist, such as in the province of Ontario. We propose a modelling approach where hourly PEFs are defined based on hourly electricity generation by fuel-type.

This paper examines how hourly PEFs affect the determination of optimized solution sets using a net-zero energy building case-study located in London, ON. PEFs are required to determine the renewable energy requirements of a source net-zero energy building. The proposed methodology determines hourly PEFs and then examines design implications using a single-objective evolutionary algorithm. Outcomes from this paper may result in improved building and community designs which better match time-varying electrical grid supply and demand.

INTRODUCTION

There is a growing need to attribute primary energy factors to site electricity consumption. Primary energy factors (PEF) are scaling factors which quantify the transformation and transmission of primary energy to delivered energy. PEFs are of significance in buildings and communities with distributed energy generation, storage and energy imports by properly accounting for renewable energy both on and off-site. In particular, the peak demand management of net-zero energy buildings (NZEBs) requires a careful consideration of instantaneous local versus centralized generation which fluctuates both daily and seasonably (Salom et al. 2011).

In the most recent US Department of Energy (DOE) NZEB definition guidelines, the accounting of energy imports and exports is handled using an averaged annual primary energy factor (DOE 2015). This may be an appropriate assumption in scenarios where single fuel type is used for generating grid electricity (common in the US); however, the application of annual PEFs may not be appropriate in locations, such as Ontario, where a portfolio of time-varying fuel-types supply electricity.

This paper aims to accomplish two tasks: (i) recommend a methodology for quantifying hourly PEFs using measured centralized electricity generation across the province of Ontario; and (ii) demonstrate how hourly PEFs impact optimized building design by better evaluating instantaneous energy imports and exports.

METHOD

The three distinct stages of the proposed methodology were: (1) determination and allocation of hourly primary energy factors, (2) case-study formulation, (3) application of PEFs using an optimization study. These approaches are described in the following subsections.

Hourly Primary Energy Factor Formulation

This paper uses the total primary energy factor (PEF) to quantify the transformation and transmission of primary energy to delivered electricity. Total PEFs account for the extraction, storage, generation, distribution and processing of electricity imported to a building. This conversion factor takes into account the energy from renewable energy sources and all energy overheads of delivery to the point of use. Table 1 shows the PEFs by fuel-type used in this research (CEN15603 2008). Note that energy resources are allocated a minimal PEF of 1.0 if they are renewable and have no transmission losses such as building integrated PV (BIPV).

Table 1: Primary Energy Factors recommended in CEN 15603:2008

Generation Type	Total Primary Energy Factor
Buiding Integrated PV	1.00
Grid PV	1.07
Wind Generation	1.07
Hydroelectric Power	1.50
Biofuel	2.00
Nuclear Energy	2.80
Gas Plant	3.31

To better quantify the instantaneous import and export of electricity to a building, this paper uses hourly PEFs as opposed a single, annual value. Hourly PEFs were determined by post-processing data published by the Independent Electricity System Operator (IESO), a non-for-profit corporate entity responsible for promoting transparency of electricity generation for the Ontario power grid (IESO 2016). The IESO publishes hourly data on electricity generation across the province of Ontario by fuel type. Figure 1 shows a breakdown of electricity generated in Ontario by fuel type for 2015. A single year was preferred over a blended average of several years of data due to the increased penetration of renewable energy in the Ontario electricity grid. This is the most conservative estimate as generation on-site will not be attributed with a high PEF if significant renewables pre-exist on the central grid.

Hourly PEFs were calculated by creating an hourly energy fraction by fuel type and multiplying the each fuel type fraction by the PEF shown in Table 1. The resulting weighted PEFs were summed across fuel types and multiplied by the building's hourly electricity consumption. Effectively, this converted site electricity consumption to source energy consumption. Similarly, if the building was net-generating electricity, the over-supply was valued using hourly PEF data. This ensured that the value of energy generated on-site was decreased if grid-electricity had low PEF values, i.e. with a large renewable fraction.

Figure 2 shows the variation of the weighted PEF for grid electricity in Ontario in 2015. Note that PEFs peak on the late winter and mid-summer and are minimal during the shoulder seasons. Typically, Ontario experiences peak generation during the summer. The winter of 2015 was an exception due to the coldest February in recorded history. This represents a more conservative estimate of PV impact on summer peak shedding.

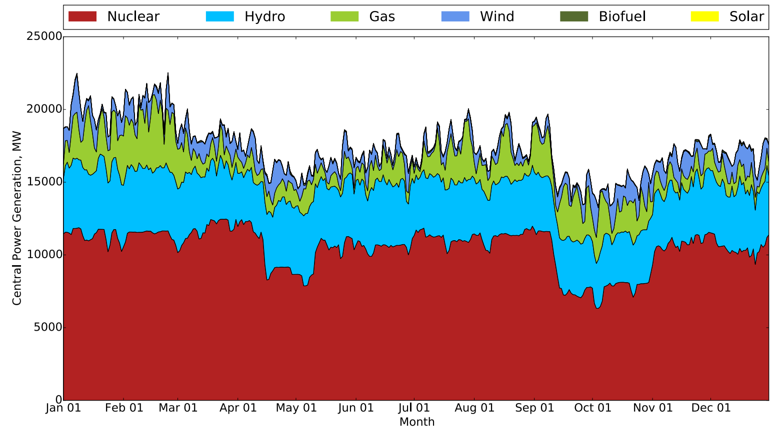

Figure 1: IESO Power Generation in Ontario for 2015

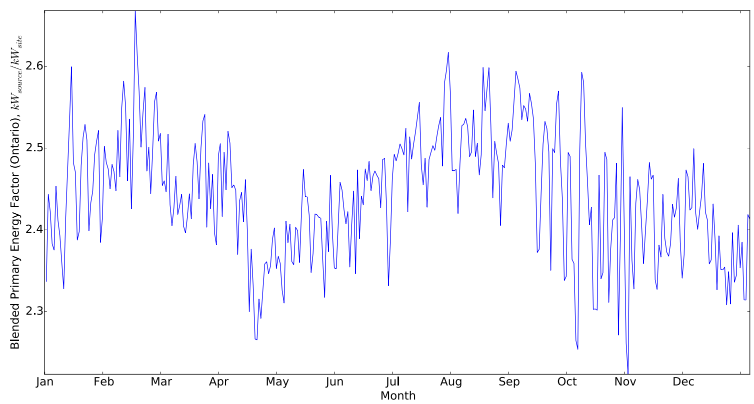

Figure 2: Daily average of hourly PEF as defined using IESO data and annual PEFs

Case-Study: A Net-Zero Energy Office Building

This paper applies the proposed methodology to a NZE office building. The building is a 3-story office building with 5,030 m^2 of gross floor area with retail space on the first floor. The design specification requires a mandatory L-shape to allow for pedestrian access to first floor retail space from both streets, see Figure 3. A primary design strategy was to identify a balance of energy conservation, energy efficiency and energy generation measures that meet a financial return on investment through improved operations.

Over 30 unique variables were considered in the office building design problem, see Table 2. A building design is defined as a unique set of building attributes or characteristics as described by these 30 design variables. Note that the approach must potentially explore over 10^{21} unique building designs for this case-study. This is called the solution space size and is calculated by multiplying the number of steps for each variable present in Table 2. However, optimization algorithms search a small portion of this total solution space to identify optimal solution sets.

Several mechanical system configurations were considered. Mechanical options included: variable-air-volume distribution with natural gas fired boilers or electric heating, package terminal air source heat-pumps (PTHP), distributed water-source heat-pumps, and a variable refrigerant flow system (VRF) (Raustad 2013). A dedicated outdoor air system (DOAS) option was considered to provide fresh-air to all spaces.

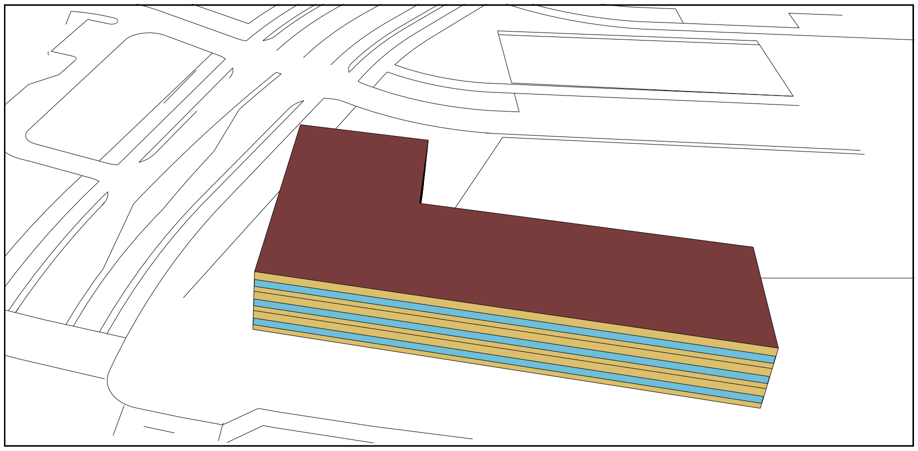

Figure 3: Rendering of preliminary office building design.

Table 2: Sample of Influential Design Variables for Commercial Office Building

Variable	Description	Units	Start	Stop	Steps
infil	Infiltration through walls: percentage compared to reference	%	75	100	8
lpd	Lighting Power Density: percentage compared to reference	%	50	100	8
eleceq	Electrical equipment power density: percentage compared to reference	%	50	100	8
azi	Building orientation relative to south	degrees	-39.4	45	16
base_ins	Basement insulation	m^2K/W	0.18	7.04	8
ceil_ins	Ceiling insulation	m^2K/W	3.52	11.40	16
wall_ins	Wall insulation	m^2K/W	3.52	10.57	8
wintyp_n	Window type north [1: Double Glz low-e. 2: Triple Glz Low-e]. Also variables for east, west, south.	–	1	2	2
wwr_s	Window to wall percentage south	%	10	80	8
wwr_n	Window to wall percentage north. Also variables for east, west	%	10	50	4
use_doas	Use a Dedicated Outdoor Air System for ventilation control	bool	0	1	2
hvac_sys	HVAC system [1: VAVelec. 2: VAV. 3: PTHP. 4: VRF]	–	1	4	4
dhw_sys	DHW system [1: DHW NG Plant. 2: DHW HP Plant]	–	1	2	2
pvbal_sc	Ballasted PV space scaling factor	–	0.1	2.5	8
pvbal_ang	Ballasted PV angle	degrees	0	35	8
pvfrac_s	PV percentage on south. Also variables for east, west, roof	%	0	80	16
pvfrac_a	PV parking lot array area	m^2	0	400	8
blind_type	Blind shading type [1: ExteriorShading; 2: InteriorShading]	%	1	2	2
blind_maxt	Max tolerable temperature in zones before blind deployment	degC	21	28	8
blind_maxsr	Max tolerable solar radiation in zones before blind deployment; 0=OFF	W/m^2	0	1400	8
dhw_ld	Percent of DHW loads relative to reference	%	60	100	8

Photovoltaic panels (PV) were the primary electricity generation strategy to achieve NZE. Building integrated PV is a proven technology which can redirect excess heat to reduce DHW and heating loads (Candanedo et al. 2010, Bucking et al. 2014). Building integrated PV was considered on the south, east and west facades as well as on the roof surface directly or on ballasted racking. In the event that additional PV was required to achieve an annual energy balance, it was placed on a racking system beside the building or on adjacent parking lot structures. The case-study used 16% efficient Photovoltaic panels.

Optimization

The inclusion of hourly PEFs complicates net-zero energy calculations. For example, the determination of energy performance now depends on how much electricity is generated, when electricity is generated and how much renewable energy exists on the grid to load balance on-site demand. This makes the design process significantly less intuitive to the energy modeller.

Optimized approaches to building design can facilitate information discovery. This paper uses a single-objective evolutionary algorithm to identify optimal solution sets. Optimization studies are conducted twice: without PEFs to determine a design baseline, and with hourly PEFs. Effectively, using hourly PEFs transformed site energy use to source energy use. The performance indicator selected for the optimization study was the net-energy use intensity (EUI), i.e. net-energy consumption divided by the gross building floor area. Of interest is how the optimal solution set changes depending whether or not PEFs are specified. Each optimization study was conducted five times to build statistically significant samples.

Optimization results are interpreted using decision trees. Decision trees are an effective means to split decision variables by the magnitude of information they add to the dataset and are used in this paper to visualize design differences when optimizing with and without hourly PEFs. A full explanation of decision trees and branching using information theory is presented in Flach (2012).

Table 3 highlights key configuration parameters of the single-objective evolutionary algorithm configuration used in the case-study. The proposed algorithm configuration aids in expediting optimization studies while improving algorithm convergence (Bucking et al. 2013).

Table 3: Summary of Single-Objective Algorithm Configuration

Algorithm Parameter	Setting
Representation	71 bit grey-coded binary string
Solution Space Size	2.36×10^{21} unique designs
Objective 1	Net-energy use intensity (with and w/o PEFs) (kWh/m^2)
Population Size	10
Recombination	50% bit-by-bit Uniform, 50% variable Uniform
Recombination Prob	100%
Mutation	40% bit-by-bit mutation, 60% differential mutation
Mutation Prob	2.0%
Parent Selection	Tournament selection
Elitism?	Yes, best individual
No. of Children	10
Survivor Selection	Best parents and children, $(\mu + \lambda)$
Diversity Control	Average number of bits shared with elite individual

A 71-bit binary representation was necessary to represent the variables ranges described in Table 2. Binary representations improved algorithm convergence properties with the trade-off of losing resolution in variable ranges. A differential mutation operator, originally created by Storn & Price (1995), was adapted to work within a binary evolutionary algorithm. This operator was found to improve convergence properties of the optimization algorithm (Bucking et al. 2013).

RESULTS AND DISCUSSION

Figure 4 shows the site EUI optimization data separated by azimuth. This plot shows net-present values versus EUI to separate data throughout the convergence path. Pareto fronts were not formed since a single-objective evolutionary algorithm was used. The domain of the set ranges from 160 kWh_{eq}/m^2 to -1 kWh_{eq}/m^2 which suggests net-generating designs were possible using the design parameters suggested in Table 2.

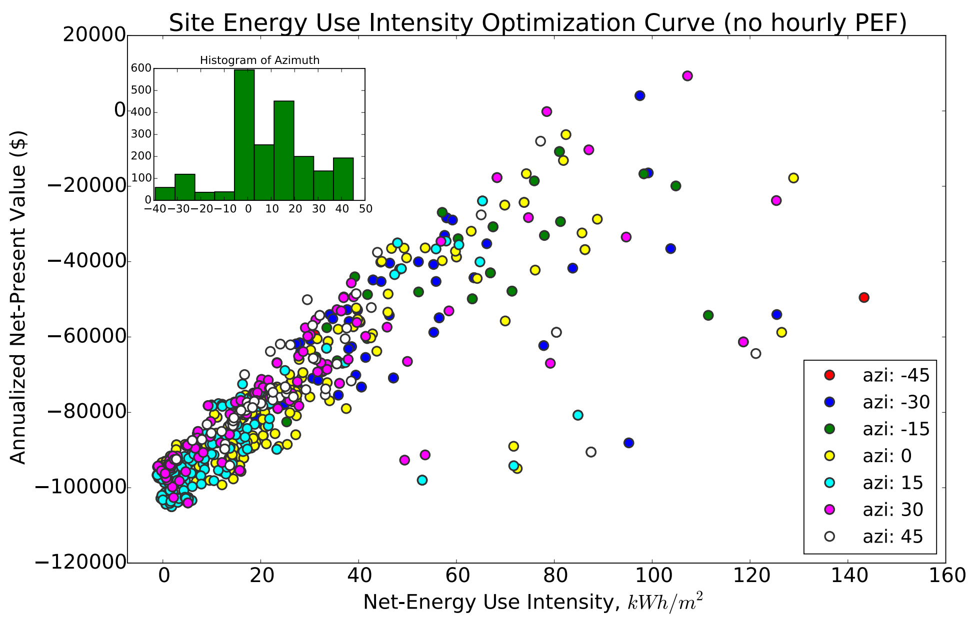

Figure 4: Source Energy Use Intensity Optimization (no PEF)

Figure 5 presents the decision tree of the optimized site energy dataset (no PEF). Decisions trees can be interpreted as follows: the root or top of the tree includes the whole set, each subsequent bifurcation represents a subcategorization of the set divided by the significance of the design parameter (Table 2), EUI increases as the tree is traversed from left to right, each node or circle shows the average EUI and the number of representations (n) in the subset, and trees are trimmed after a specified depth (in this case a maximum depth of seven nodes). This plot was created using a reduced set of data (3rd quantile) to explore design trade-offs. As the set is further reduced to the 1st and 2nd quantiles, additional structure and thus information is required to visualize the growing number of design trade-offs. Note that the optimized dataset is split by electrical plug-loads, mechanical system type, lighting power density and insulation levels.

Statistical analyses were conducted using a regression analysis with generalized linear regression models (GLM) to identify the relative importance of each variable shown in Table 2 on the performance outcome. The GLM used a Gamma distribution with a shape factor of 1.0 for the statistical fit. Table 4 shows the relative significance of each decision variable for the

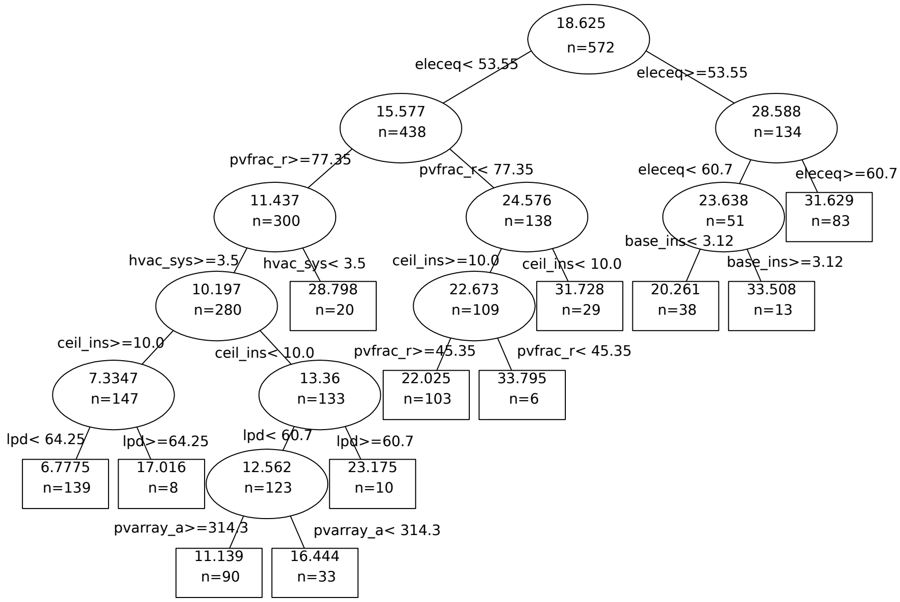

Figure 5: Decision Tree for Site Energy Optimization (Units kWh/m^2)

site EUI (no hourly PEF) optimization study.

Table 4: Ranking of Top-Five Influential Variables in Site Energy (no hourly PEF)

Rank	Description	Units
1	PV Fraction on Roof	%
2	Mechanical system Type	–
3	Size of PV Array on ground	m^2
4	Plug load fraction (compared to ASHRAE 90.1)	%
5	Lighting Power Density fraction (compared to ASHRAE 90.1)	%

Figure 7 presents the decision tree of the optimized hourly PEF or source energy dataset. This decision tree considers a sub-set of the data from 1.1 to 80.7 kWh/m^2 to explore the structure in the set.

Figure 6 shows the source EUI optimization data (with hourly PEF) separated by azimuth. The domain of the source EUI set ranges widely from 300 kWh_{eq}/m^2 to -1 kWh_{eq}/m^2. This figure suggests that net-zero energy performance targets are possible in Ontario for a commercial building archetype even when considering the variety of fuel-types for grid electricity generation.

The histogram of Figure 6 shows the frequency of azimuths found in the optimization set. A preference emerged for orientating the building approximately 40 degrees away from south. This was due to an underlying trade-off of improved passive solar performance (south orientation) versus improved attribution of PV generation on east and west facing surfaces. A likely cause is that the algorithm is determining times of day with peak fossil fuel generation and offsets using using PV generation which is given a low PEF value during electricity export (recall BIPV has the lowest PEF of all generation types).

Table 5 shows the relative significance of each decision variable for the source EUI (with hourly PEF) optimization study using a GLM.

Comparing decision trees in Figures 5 and 7 shows the internal structure of the optimization set differs when using hourly PEFs. The site-EUI optimization set (no PEFs) was

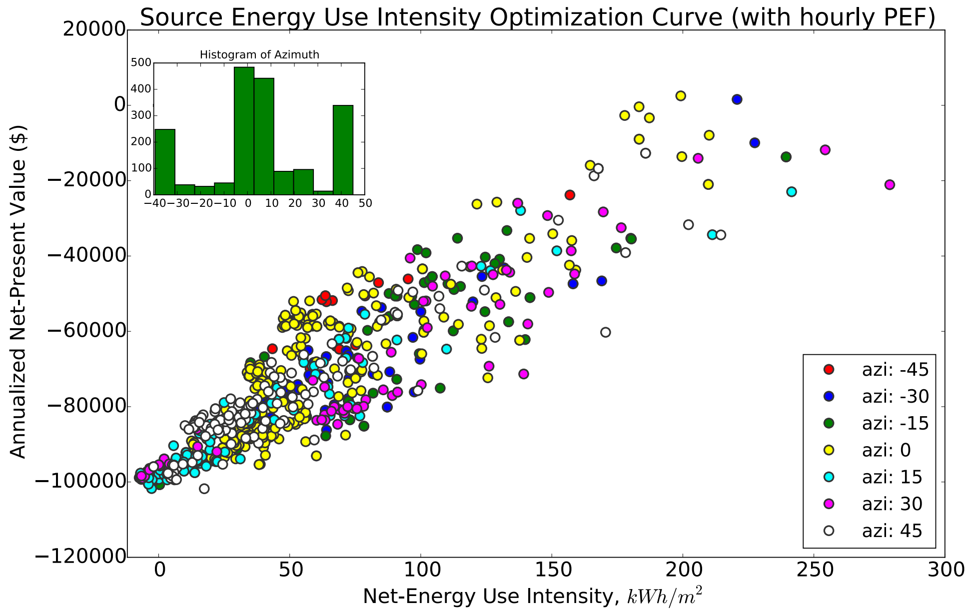

Figure 6: Site Energy Use Intensity Optimization (hourly PEF)

Table 5: Ranking of Top-Five Influential Variables in Source Energy (with hourly PEF)

RANK	DESCRIPTION	UNITS
1	PV Fraction on Roof	%
2	Plug load fraction (compared to ASHRAE 90.1)	%
3	Building Orientation	deg
4	PV Fraction on East Facade	%
5	Window to Wall Ratio (East and West)	%

split by selection of mechanical systems, insulation levels, plug-load reduction strategies and lighting power densities. When using hourly PEFS, the set is split primarily by the size and orientation of BIPV, plug-loads reduction strategies.

CONCLUSION AND FUTURE WORK

This paper showed the importance of considering hourly PEFs during the preliminary design process of a building. Hourly PEFs were created for the Ontario power grid by post-processing IESO data for several fuel-types and applying annual primary energy factors using European standards. This assessed the effective value (from the grid perspective) of hourly energy use and generation for a commercial NZEB case-study. The proposed methodology can be reproduced for other geographic locations, but the results and case-study are only applicable to the province of Ontario.

Using an optimization methodology several key differences were found between the site-energy and source-energy scenarios. Although additional analyses are required to describe the root cause of discrepancies in optimized sets, it is clear that the use of PEFs result in differing design recommendations.

Future work can be summarized as follows: (i) explore the implications of additional technologies such as combined heat and power on managing hourly energy imports, (ii) explore the control sequencing of storage and generation to further reduce primary energy use intensity, (iii) apply other visualization or machine learning techniques to more deeply compare optimized design datasets, and (iv) scale the proposed methodology to a community-scale case-study.

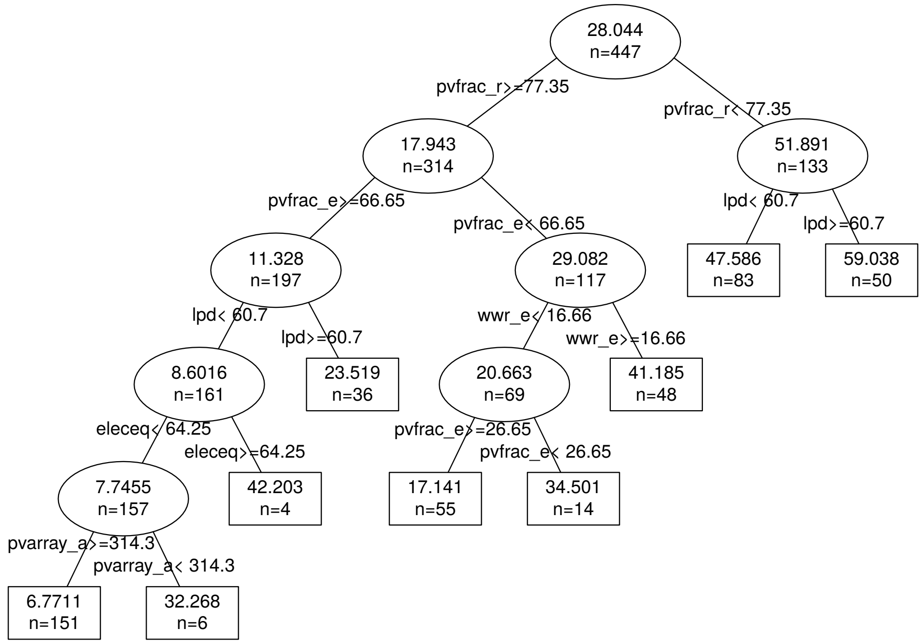

Figure 7: Decision Tree for Source Energy Optimization using hourly PEFs (Units kWh/m^2)

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