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The impact of urban texture on energy system design process

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The impact of urban texture on energy system design process

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Abstract. This study evaluates the impact of urban planning decisions regarding building stock on energy system design and operation. Three urban planning scenarios are considered for an archetype neighbourhood in Nablus in Palestine. The distinguishing difference is that they have different albedo values for the building stock. A computational platform that combines building simulation, urban climate and energy system optimization (considering Net Present Value (NPV) and Grid Integration Level) is used to assess the scenarios. The study reveals that the annual or peak energy demand is not sufficient to compare two scenarios; it is important to consider energy demand pattern and the renewable energy potential, where an energy system design tool is important. Therefore, it can be concluded that the energy system design tools will play a major role in sustainable urban planning processes.

1. Introduction

Rapid depletion of fossil fuel resources, climate change and escalating urban populations make it essential to improve the energy efficiency and sustainability of urban energy infrastructure. However, this is a challenging task which requires the support of multiple parties with different expertise [1]. When considering the demand side, people are often interested in the energy efficiency at building scale. The thermal impact of buildings on the neighbouring buildings and the urban microclimate are often neglected resulting in decreased opportunities to improve the energy efficiency of the urban configuration [2]. Furthermore, improvements in energy demand and generation are conducted separately without much coordination. This makes it important to develop a holistic framework to design energy infrastructure considering different aspects in order to improve the efficiency and sustainability of urban energy infrastructure [3].

Towards achieving this goal, it is important to develop a holistic urban energy model combining building simulation, urban climate simulation and energy system optimization [4]. Such a holistic approach can help to quantify the importance of each factor and subsequently optimize the energy efficiency and sustainability. This study tries to demonstrate the importance of such a holistic approach in an urban context. It specifically focuses on evaluating the impact of albedo values of the building stock on the energy infrastructure. The impact of the albedo values of external surfaces has been considered in a number of studies for a single building from the perspective of energy demand. For example, the impact of albedo values on the peak and annual energy demands has been studied in References [5–9]. Integrating materials with higher external reflectivity has been recommended as a method to mitigate adverse effects due to the urban heat islanding effect [5]. However, the influences of the albedo values on urban climate, energy demand and more importantly the energy system have not been studied. Building energy demand and urban climate are closely coupled together due to the notable impact of the building stock on the urban climate [10]. Subsequently, energy demand of building stock is linked with energy system designing process. Hence, it is important to consider the close relationship between energy demand, urban climate and energy system sizing. Towards achieving this objective this study uses a holistic platform combining building simulation, urban climate and energy system optimization. The research paper is arranged in the following manner; Section 2 of this paper presents the methodology used in this study. A brief overview of the building simulation model, urban simulation model and energy system optimization is presented in this section. Section 3 presents the results of the study and the discussion.

2. Methodology

A computational platform is developed in this study to consider the influences of building energy demand, urban climate and energy system design. When considering these three, building energy demand and urban climate conditions are closely coupled with each other. The surface temperature of the building stock influences both the energy demand of the building and the temperature and wind speed in the urban canopy layer. Magnitude and the fluctuations in the energy demand influence the energy system design process. This makes it important to have a holistic platform considering urban climate, building simulation and energy system optimization.

Considering urban climate and energy demand in the urban building stock is a challenging task due to the strong coupling between them. Currently, the combination of macro-scale meteorological models with building simulation models fails to present the drag force effect and generated turbulence [10]. Furthermore, most of the building simulation models neglect the influence of shadowing and boundary layers. Hence, these models fail to represent the urban heat islanding and cooling pool effect [2,11]. Failure to present such phenomena will lead to a significant performance gap in energy system operation [4]. Although computational fluid dynamic (CFD) models are a better way to improve the accuracy, such models take much more computational time, especially when simulating results, and it is thus computationally challenging to conduct yearly time series simulations. The Canopy Interface Model (CIM) [12] becomes an attractive solution in such instances to reduce the computational burden while accounting for local scale urban phenomena. Hence, this study combines CIM with CitySIM [13] a building energy model. CitySim can model the energy demand of a building stock (representing each building through a single zone) while considering the radiation heat transfer among the buildings. The influence of the urban climate is introduced to the CityCim model through a coupling with CIM.

2.1 Coupling between CitySim and CIM models

CIM is a 1D urban canopy model which can be used in an offline mode. It resolves the flow in the vertical direction and computes values for the wind speed in the x and y direction as well as the air temperature. For each calculation, the column module can be forced with values for the top most column and with the surface temperature for the ground and for the obstacles present. The obstacles are represented as occupied surfaces and volumes and their dimensions can be specified for each level of the module, giving an improved representation of the surface in the mixing length and drag force calculation.

CIM has been coupled with CitySim to improve the boundary conditions in both models [11]. In the first iteration, CitySim is run with standard meteorological data (such as given by Meteonorm [14]) to obtain the surface temperatures. The surface temperatures obtained as well as the wind speed and air temperatures are then used as boundary conditions for CIM. The output from CIM including the *"urban effect"* is then used as input for CitySim to calculate the energy demand.

2.2 Simulation case study

The case study is conducted for Nablus, a city in Palestine. The city of Nablus (32°13' N, 35°16' E) is situated in the northern part of the West Bank and it presents a Csa climate (C: temperate; s: dry summer;

a: hot summer). The city is located at 550 m above the sea level and it presents a particular topography, as it is positioned in a narrow valley, between the Mount Ebal and Mount Gerizim. In this paper, the study focuses on the Al-Habaleh district, within the old city, characterized by dense constructions and narrow streets. The physical and geometrical data required for setting up the model were previously defined [15]. The meteorological data are provided by the tool Meteonorm [14], representing a Typical Meteorological Year (TMY). In order to understand and to quantify the impact of the radiative environment on the CIM model, as well as on the energy demand (for heating and cooling) of buildings, the global albedo of the site was varied from 0.1 to 0.8. Figure 1 shows the 3D model of the city, as designed according to the proposed methodology, where the geometrical properties of the city are redesigned as a function of its density.

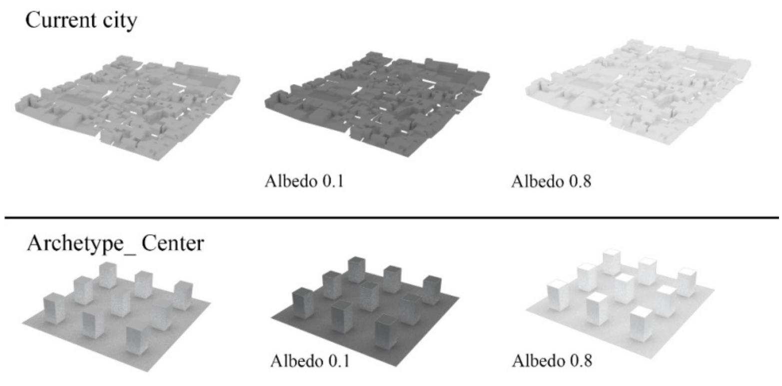


Figure 1. 3D model of the city of Nablus. Current city design and proposed geometrical model

2.3 Computational model for energy system optimization

Multi-energy hubs catering electricity, heating and cooling demand of the location are considered in this study [16–18]. The energy hub consists of renewable energy technologies such as solar PV (SPV) and wind turbines. An internal combustion generator (ICG) and a battery bank are considered as dispatchable source and storage. Heat-pumps and air-conditioners are used to cater the heating and cooling demand of the building stock respectively, which converts the heating and cooling load to an electricity demand. The energy hub interacts with the medium voltage grid when catering the demand of the energy hub. Curtailments are introduced for both selling and purchasing electricity to and from the grid in order to maintain the stability of the grid. A computational model is developed to model the energy and cash flow of the system. The computational model is assisted by hourly simulation to map the decision space variables into the objective space. Hourly wind speed, solar irradiation, as well as energy demands for cooling, heating and electricity are taken for the simulation of the energy system considering a time period of one year. Power generation from the wind turbines (P_t^{Wind}) and SPV panels are computed using Eq. (1-2) for time step t.

$$P_t^{SPV} = G_t^{\beta}\,\eta_t^{SPV}\,A^{SPV}\,x^{SPV}\,\varsigma,\quad \forall t \in T \tag{1}$$

$$P_t^{Wind} = \tilde{P}_t^{W}(\mathrm{v}_t)\ \mathrm{x}^{\mathrm{w}}\ \eta^{\mathrm{Losses}},\forall t \in T \tag{2}$$

In Eq. 1, G_t^{β}, η_t^{SPV}, A^{SPV}, x^{spv} and ς denote the global solar irradiation on the tilted PV panel, the efficiency of the SPV panel, the number of PV panels obtained using the optimization algorithm. In Eq. 2, X^{w} and η^{Losses} denote the number of wind turbines in the system (which is obtained using the optimization algorithm) and the power losses. The Durisch model [19] is used to consider the SPV panel efficiency considering the global solar irradiation on the tilted SPV panel, cell temperature, and air-mass is used to compute the efficiency of the SPV panels.

Grid integration level (GI) and net present value (NPV) of the system are considered as the objective functions for the optimization problem. Grid integration level presents the autonomy level of the energy system and often used as an objective function in the multi-objective optimization of energy system along with the cost [16]. Grid integration level is formulated according to Eq. 3.

$$GI = \sum_{\forall t \in T} P_t^{IG} / \sum_{\forall t \in T} E_t^{D}, \forall t \in T \tag{3}$$

In this equation, P_t^{IG} and P_t^{D} present the energy imported from the grid and the demand of the energy hub. The net present value (NPV) of the system is modelled in a similar way after considering initial investment and present value of all the operation and maintenance costs. A bi-level dispatch strategy based on fuzzy automata theory is used to consider the operation of the internal combustion generator, energy interactions with the battery bank and the grid. A detailed description of the dispatch strategy can be found in Ref. [16]. A Pareto multi objective optimization is conducted using evolutionary algorithms. A comprehensive explanation of the demand profiles, renewable energy potential and its impact on the energy system via microclimate was previously presented in Ref. [4]

3. Results and discussion

The energy demand of the archetype building stock is computed considering three albedo values. Subsequently, the demand profile for heating and cooling is assessed in Section 3.1 and the impact of the demand profile is assessed in Section 3.2.

3.1. Demand profile for the three scenarios

The hourly heating and cooling demand profiles are presented in Figure 2. When analyzing the heating and cooling demand profiles it is clear that a higher albedo ratio will result in a significant reduction in cooling demand as reported in the literature [5–9]. However, it will also increase the heating demand, especially during the winter period. The influence of the albedo value on the cooling demand is visible when analysing both peak and annual cooling demands (Table 1). A significant reduction in both peak and annual cooling demands has taken place due to the changes in the building external surface. The peak cooling demand has decreased from 870 kWhs to 247 kWhs while the annual cooling demand has decreased from 886 MWh to 72 MWH when moving from Scenario A (albedo of 0.1) to C (albedo of 0.8). However, the influence of albedo values on the peak and annual electricity demand behaves in a different manner since it considers catering both heating and cooling demands using heat pumps and air-conditioners. A notable reduction in both peak and annual electricity demand can be observed when moving from Scenario A to C. However, the lowest peak and annual demand can be observed in Scenario B (albedo of 0.58). This can be explained by considering the heating demand. Although higher albedo values can help to minimize the cooling demand it will increase the heating demand during the winter since it minimizes the solar heat gain during the winter. A moderate albedo will balance both heating and cooling requirements such as in scenario B, reducing both annual and peak electricity demands (such as Scenario B).

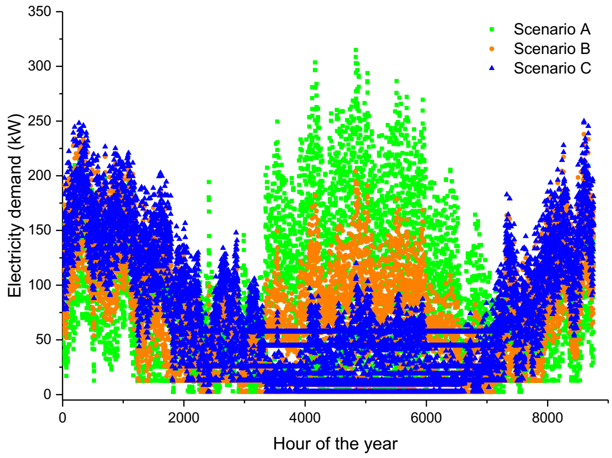


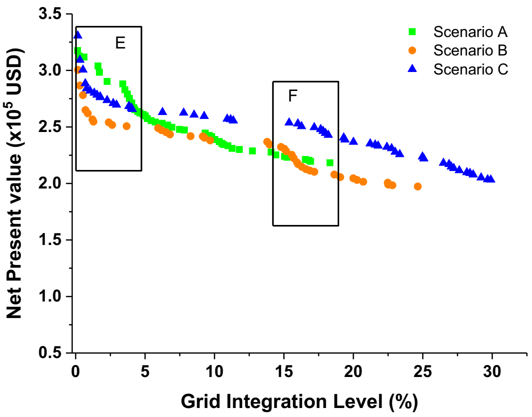
Figure 2. Hourly variation of electricity demand after converting heating and cooling demands into electricity

Table 1. Peak and annual electricity and cooling demands for the three scenarios

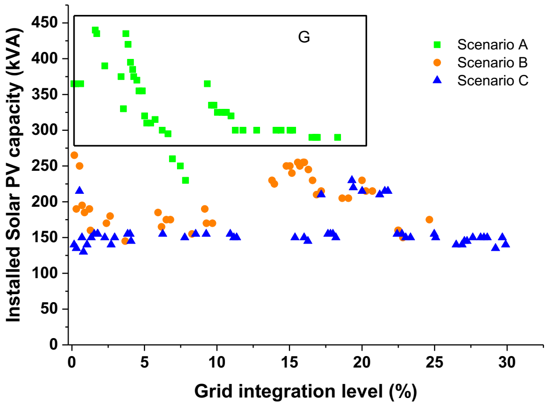
	Annual electricity demand (considering heat-pumps and air conditioners) (MWh)	Peak electricity demand (kWh)	Annual cooling demand (MWh)	Peak cooling demand (kWh)
Scenario A (Albedo 0.1)	713	315	886	870
Scenario B (Albedo 0.58)	636	237	324	540
Scenario C (Albedo 0.8)	652	250	72	247

3.2. Pareto fronts for the three scenarios

Pareto fronts obtained using multi-objective optimization for the three scenarios are presented in Figure 3(a). When analyzing the three Pareto fronts it is observed that Scenario B represents the lowest cost although it is not the one having the highest albedo ratio. However, the comparison of the Pareto fronts for Scenario A and C brings quite an interesting observation. Pareto solutions of Scenario C outperform Scenario A for a part in the Pareto front when the grid integration levels are low (as marked in Box E). However, the conditions totally change when increasing the grid interaction levels further. Pareto solutions of Scenario A outperform Scenario C with a notable cost margin especially in the sections within Box F. Scenario A has a peak and annual electricity demand respectively 20% and 8.5% higher than Scenario C. Even after catering such a high energy demand, the Pareto solutions for Scenario A can maintain a lower cost compared to Scenario C except for the part marked in Box E. To understand the situation further, installed SPV capacities are plotted for the three scenarios (Figure 3 (b)). Figure 3b clearly shows that installed PV capacity for Scenario A is notably higher when compared to Scenario C (highlighted in Box G). As a result, there will be higher PV generation during the summer period which will be relatively cheaper (due to the abundant solar energy potential). The excess SPV generation will compensate the higher cooling demand due to lower albedo value. Therefore, the net present value of the design solution for Scenario A becomes cheaper when compared to Scenario C. When considering Scenario A and C it can be concluded that a minimum demand scenario might not be the optimum for the energy system; especially when considering the seasonal variation of the renewable energy potential. Hence, it is important to consider the urban planning scenarios along with energy system designs besides being limited to minimizing the energy demand. This will make it important to have holistic design platforms that consider building simulation, urban climate and energy system design.



(a)



(b)

Figure 3. (a) Pareto fronts for the three scenarios and (b) installed SPV capacity for the Pareto solutions

4. Conclusion and outlook

The study reveals that changing albedo values of the building stock can help to reduce the cooling demand. When considering the annual energy demand having a moderate albedo value will be helpful when considering both heating and cooling energy demands. When comparing the Pareto fronts obtained for Scenarios A and C it is revealed that reduction in annual or peak demand itself will not guarantee a cost reduction for the energy system. It is important to consider the demand pattern as well as the potential for renewable energy sources. This makes it important to have an energy design tool embedded into the urban planning process.

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