INFOMORPHISM: URBAN PLANNING FOR RENEWABLE ENERGY INTEGRATION VIA SIMULATED ENERGY EXCHANGE NETWORKS

Fengqi Li
Alexandros Tsamis

Department of Architecture
Center for Architecture Science and Ecology
Rensselaer Polytechnic Institute
110 8th St, Troy, NY, USA
Lif4@rpi.edu

Kristen R. Schell

Mechanical & Aerospace Engineering
Carleton University
1125 Colonel By Dr, Ottawa, ON K1S 5B6, CANADA
kristenschell@cunet.carleton.ca

ABSTRACT

Increasing renewable energy efficiency is a crucial part of developing a sustainable city. While current Urban Building Energy Modeling frameworks have been developed for analyzing and improving urban energy efficiency, these tools have not integrated systemic optimization modeling to develop and evaluate the performance of potential urban environments from generative planning models. In this study, we present Infomorphism, a computational planning framework that joins a morphological generative process with an energy network optimization model, to explore potential planning policies and constraints associated with renewable energy integration. This paper takes Manhattan as a case study to show local energy networks that maximize the city's overall efficiency to share local renewable energy - generated thermal and electric energy - maximize renewable energy penetration rates and minimize energy exchange costs. We show how geothermal and solar drive a future city's collective form and infrastructure to achieve up to 74% local renewable energy integration.

Keywords: urban planning, network optimization, multidisciplinary design optimization, urban scale modeling, renewable energy integration**.**

1 INTRODUCTION

Urban planning emerged to ensure basic rights - such as rights related to transportation, access to sanitary infrastructure, access to light and fresh air, just to name a few. Rapid population growth, coupled with global urbanization, is forcing urban designers and planners to address anthropocentric global climate change, with a recognition that improving the energy performance and efficiency of a city would achieve the largest reduction in greenhouse gas emissions. To increase urban energy efficiency, a much greater level of renewable energy must be planned for and integrated into a city's form and infrastructure. Designing such a city is a large-scale, systems-level challenge, as optimal renewable energy integration will affect everything from the building envelope design to the zoning regulations of city blocks. Currently, however, renewable energy integration in cities is focused on the building or neighborhood level and has not yet been well-studied at the urban planning level.

1.1 Recent Advances in Building-Level Renewable Energy Integration

At the building level, there have been many different modeling efforts and software platforms designed to increase energy performance. For example, Zero Energy Buildings (ZEBs) (Derkenbaeva et al. 2022) improve renewable energy integration at the building level. ZEBs are energy optimized buildings deployed with integrated technologies that can optimize energy efficiency production and consumption in an effort to reduce if not complete eliminate the buildings reliance on the electric grid. Many studies have developed integrated building technologies to optimize renewable energy generation. For example, Barone et al. designed a Concentrating Photovoltaic glazing (CoPVG) system for smart building facades to actively generate electricity and heat (Barone et al. 2022). They also developed a simulation tool to analyze the energy performance of the system. Liu and Wu developed a Building Integrated Concentrating Photovoltaic (BICPV) window system with a Hydroxypropyl Cellulose (HPC) based thermotropic hydrogel membrane, to optimize the electricity generation on the building façade system; the BICPV also serves to control indoor heat gain and lighting within the building (Liu and Wu 2021). Tsamis et al. proposed an ectothermic approach for heating and cooling in buildings to allow buildings' envelope systems to actively regulate heat exchange, in dynamic response to their surrounding environment. (Tsamis et al. 2020). Other studies (Setlhaolo et al. 2017, Xu et al. 2019, Niu et al. 2019) have transformed buildings into energy hubs to manage the use of renewable energy and to efficiently use buildings as both thermal and electric battery storage. This transforms the role of ZEBs from consumers to that of "prosumers" of energy in a city. When these buildings are connected via an energy exchange network, such as the existing electric grid or district heat network, they can share their surplus renewable energy with their neighbors. The development of local energy exchange networks pushes the boundary of urban planning to implement new policies or planning restrictions in regards to emerging energy rights.

1.2 Renewable Energy Integration in Neighborhoods and Cities

At the neighborhood level, there has been significant research on designing and planning buildings and neighborhoods to increase local renewable energy generation and energy efficiency, with a focus on reducing reliance on the central electric power system. Singh and Gu reviewed common generative design frameworks that created tools using cellular automata, genetic algorithms, L-systems, shape grammars, or swarm intelligence (Singh and Gu 2012). Shi et al. reviewed generative urban morphological design frame- works integrated with simulation components (Shi et al. 2017). Nagy et al. created a generative framework to optimize solar panel distribution across building rooftops in a neighborhood (Nagy et al. 2018). These studies, however, have been limited to the neighborhood level and changes to the urban fabric that would improve renewable energy generation and efficiency have not been explored. Further research projects have developed simulation-design frameworks using multi-objective optimization approaches to improve the energy performance in urban community developments. Wilson et al. (Wilson et al. 2019) produced a comprehensive design framework to generate masterplans based on the correlation of various urban factors, such as urban density, building configurations, and street networks. Kosicki et al. (Kosicki et al. 2019) developed a multi-objective optimization system called Hydra to generate massive masterplans and evaluate the performance of the forms based against various metrics (e.g. daylight potential, quality of view, solar radiation). However, the introduction of a local energy exchange network in these urban designs could re- define the fundamental constraints and regulations of the aforementioned frameworks. For example, if the absorbed solar energy on rooftops could be exchanged among neighborhoods, the best building form in that project may change dramatically as a response to the changing planning regulations. For all these developing research projects, the updated planning policies, for example, regulations in terms of energy rights, would drive different decisions and different results.

Another field of research has focused on developing local energy infrastructure, or microgrids (MGs) (Lasseter and Paigi 2004), which can be incorporated into a centralized power system. Microgrids are one component of Smart Grids (SGs) (Strasser et al. 2015), which have increased communication and control strategies between the centralized and decentralized systems. Increasing microgrids, or local electric networks, could serve to increase the exchange of renewable energy generation and use. In parallel with the field of SGs, different Urban Building Energy Modeling (UBEM) approaches have been developed to analyze the smart energy networks and systems in relation to the buildings. Ferrando et al. reviewed eight state-of-the- art UBEM tools and compared these tools based on five feature categories (Ferrando et al. 2020). Ali et al. used qualitative and quantitative analysis to review different top-down and bottom-up UBEM approaches and proposed strengths, weaknesses, and potential steps to take for each category (Ali et al. 2021). The general workflow of a bottom up UBEM tool requires collecting data from an existing urban environment. Analyzing these data is a process of creating new understandings of encoded environments. The results from these analytical processes could contribute to generating various planning constraints for further urban developments. However, the current UBEM workflow cannot allow users to encode an urban environment as a spatial input directly from generative models for further analyses. This disconnection between generative design and UBEM frameworks could either make less comprehensive understanding of the issues related to urban energy system or provide less precise urban typologies towards an optimal solution. For further development of an UBEM tool, the integration of the two fields could allow a general planning framework to have optimization components to negotiate an urban environment and its energy performance with constraints from various data-driven analytics.

1.3 City-Level Simulation Modeling

For example, the City Buildings, Energy, and Sustainability (CityBES) platform developed at the Lawrence Berkeley National Laboratory (Chen et al. 2017) is a web-based computing environment to analyze multi-scale energy efficiency issues through urban building energy models using EnergyPlus (Crawley et al. 2000) and existing urban data. Each workflow in this platform provides a data-driven approach for analyzing urban energy-related problems through a joint-simulation method. The framework does not include optimization components to receive future changes in a city. Decisions made based on the analyses of the current state of a city might not be ideal for energy optimization when compared to what the city "could" be from a long-term planning perspective. For example, in some of the case studies, the CityBES framework builds an existing city model in which buildings are a priory considered end-users of energy, and the primary energy system for the city is a priory decided to be a district energy system. In this case, the typical energy system proposed by the CityBES excludes the possibility of a hybrid energy system that includes both local energy exchange networks as well as district ones. To meet the heating demand, the heat energy flows were transformed from the central power plants to the end-users (Li, Hong, and Zhang 2021). However, if integrating local energy networks at the building level is a possible scenario for a city, the joint, simulation-based platform does not provide components to efficiently adjust the settings with the changing scenario.

Another bottom-up data-driven approach, the Urban Renewable Building and Neighborhood optimization (URBANopt) project (Kontar et al. 2020), developed at National Renewable Energy Laboratory (NREL), provides a software development kit (SDK) for high-performance energy districts. The SDK provides flexible workflows to analyze district thermal and electric systems, high energy-efficient buildings and the interaction among district thermal and electric systems, high energy-efficient buildings, and the central grid. However, the goal of this project is not to provide a front-end user interface and address specific urban design and planning issues. Rather, the objective was to establish an SDK for modeling the high-performance buildings and energy systems at a district scale (Kontar et al. 2020). For example, the SDK allows users to translate spatial data in a cohesive development environment including modules, such as EnergyPlus and OpenStudio, and generate new workflows for energy system design and analysis. Although the URBANopt framework provides a workflow for connecting multiple simulation tools, the tool kit does not develop an interface for connecting with generative models. In other words, the SDK has not been conceptualized as a spatial design tool that allows for designers and planners to make design decisions. It would be valuable to expand the capacity of the SDK to include generation and optimization modules for analyzing interactions between ZEBs and emerging urban energy systems.

1.4 Contributions

This study develops a new computational urban planning framework, entitled Infomorphism, which simulates new energy-integrated urban planning envelopes and studies the local energy network design optimized for each. Through a generative process a multitude of urban planning envelopes are first encoded into a dataset and then utilized as input for a local energy network optimization model. The Infomorphism frame- work establishes three primary components to simultaneously address urban morphology and local energy exchange network optimization. Firstly, a generative process for urban planning maximum envelopes is developed, which optimizes the implementation of current Floor Area Ratio (FAR) codes for each city block as well as decides on function distribution within the designated area. The goal of this optimization is to maximize renewable energy generation at the building level. Secondly, a new machine learning model is developed and validated to predict the total energy demand of each proposed maximum planning envelope in the city. Thirdly, a local energy network model is developed to identify an optimal renewable energy exchange network design between blocks. Taken together, these components comprise a joint simulation and optimization modeling framework, to study how ZEBs (the capacity to absorb, store, and share local renewable energy) can affect urban morphology. Results from a case study of selected districts in Manhattan show that the presence of local energy networks serve to both increase the energy efficiency of a planning envelope and reduce redundant investments in renewable generation at the building level. The effectiveness of Infomorphism as a planning framework for ZEBs is also discussed.

This paper is organized into three sections to provide a comprehensive overview of the Infomorphism framework. Section 2 describes the methods developed that support the Infomorphism framework, presenting three models: 1) a parametric model that maximizes renewable energy supply from a planning envelope and 2) an energy demand forecasting model for each planning envelope and 3) the energy network optimization model which optimizes the function of each city block, as well as the energy exchange network, per planning envelope generation. Section 3 presents and validates results through a case study, and Section 4 concludes.

2 METHODOLOGICAL FRAMEWORK OF INFOMORPHISM

The methodological framework of Infomorphism, described below, has been connected in workflow via Python.

2.1 Generating Planning Envelopes: Quantifying Renewable Energy Available per Planning Envelope

The generative urban envelope generation model is a parametric model, which translates the current urban planning regulation as design metrics and transforms urban blocks of Manhattan into what we refer to as the Energy Parcel (EP). Each EP is a planning envelope that indicates the maximum available build space within an urban block. Since every EP is controlled by certain input variables, such as the length and width of the footprint, or the location of an EP relative to the boundaries of the city block, the parametric model can produce variations from a generative process by recording the values of these variables. The parametric model can store on EPs basic properties, such as Footprint, Height, Floor Area Ratio (FAR), and Land Function. In our case, we used a Grasshopper inside Rhino (McNeel et al. 2022) to output the encoded Eps in an Excel sheet. We refer to the collection of all EPs as an EP Neighborhood (EPN). As a result, a selected area of Manhattan can be translated into an EPN dataset.

An energy quantification model can quantify the total renewable energy potential of EPNs by considering every EP separately while taking into account its immediate neighbors. So far, we have defined two different renewable energy resources, solar and geothermal, as primary drivers for generating EPNs. For Solar, we quantify the solar energy potential of an exposed surface and direction to the sun. By applying specific available building-integrated solar technologies and using as input each of the EPs, the form of all its immediate neighbors, and the local weather data, the quantification model outputs a theoretical solar energy supply based on the specific shape and orientation of each EP. In our case, we assumed that the roof area of each EP would be installed with photo-voltaic/thermal (PV/T) collectors (Buker and Riffat 2015) and the vertical surfaces would be integrated with the concentrating photovoltaic and thermal collectors (BITCoPT) (Novelli et al. 2021). We used Ladybug & Honeybee (Roudsari and Roudsari 2013), an environmental analysis plugin for Grasshopper within Rhinoceros (McNeel et al. 2022), to calculate the solar radiation reaching the surface of EPs, and the simulation results were saved to the previous Excel sheet.

For geothermal energy, analytical models (Nian and Cheng 2018, Soltani et al. 2019) exist that describe the relationship between a borehole temperature and depth, the pump capacity of the geothermal technology, and the configuration of an EP. The location, number of geothermal holes, and associated geothermal technologies all become decision variables for quantifying the geothermal potential of an EPN. In our case, we selected a single 10 MW average heating capacity geothermal system, which can generate nearly 2.092e8 KBTU per year (Durga et al. 2021), as input to determine which EP may need extra geothermal energy. In order to determine energy preference between Solar and Geothermal, the Infomorphism framework uses the capacity-weighted levelized renewable energy cost (United States. U.S. Energy Information Administration EIA) for both and decides for each EP separately which energy source should be privileged.

With the generated EPN data, the Infomorphism framework provides an energy forecasting model to predict the energy demand of EPs based on their spatial properties. In our case, we took the Pluto data (NYC Department of City Planning) and energy and water data for the year 2020 (NYC Office of Climate & Sustainability) as input data for understanding the relationship between the current building thermal and electric energy consumption and building properties, including total floor area, zoning type, and building function. We applied Gradient Boosting Tree regression (GBTR) algorithms (Touzani, Granderson, and Fernandes 2018) to predict the population density and energy consumption intensity (EUI) for heat and electricity. For the GBTR forecasting model, the random sampling rate of training data is 70%, and the rest 30% of the shuffled data are used for validations. To ensure the robustness, the adopted model is trained and validated for 30 times based on different subsets of the shuffle dataset and the model with smallest error have been saved for predicting energy demand profiles. In this case, each EPN datasheet could have an energy demand section for every EP.

2.2 Local Energy Network Optimization Model

A local energy network optimization model, described mathematically below, identifies the optimal energy exchange network for each EPN. The optimization model takes as input the EPN data generated from the simulation process described above. In particular, the energy network model is parameterized by the annual supply of renewable energy available in each urban parcel $kc_{k,n}$, as well as the energy demand needed for the building envelope on that parcel. The renewable energy supply available at each parcel can be enhanced through investment in infrastructure to exploit the geothermal resource, which could be enough to enable the parcel to become self-sufficient, supplying all energy necessary to meet demand. However, if it is better according to the objective function and related constraints, the parcel could forgo additional investment in supply and instead procure unmet demand from the local energy network to be optimized, or the central grid. Nodes in the local energy network are defined by intersections of the existing street network. As a multi-objective optimization model (Equation 1), the local energy exchange network is designed considering the multiple facets of the problem, including: maximizes the selected land use percentage, maximizes the energy flow from supply nodes to demand nodes, while also minimizing the cost of exchanging energy over the network, purchasing energy from the grid, utilizing the geothermal energy with minimum electric consumption, and managing the use of solar energy. The objective function could be easily adapted for future studies, to include other concerns from urban planners.

This model is formulated as a multi-objective, mixed-integer linear optimization model. It was written in Python (Van Rossum and Drake Jr 1995), utilizing the Pyomo and NetworkX modules, and solved with the glpk optimization solver (Bynum et al. 2021, Makhorin, A. 2020). The sets, parameters, decision variables, objective function and constraints of the optimization model are described below.

Nomenclature

Parameters

$bM_{k,n}$	Maximum allowed geothermal systems at parcel k, in network n
$bt_{k,n}$	Geothermal energy supply per unit at source node k, in network n [$kBtu$]
$c_{i,j,n}$	Energy exchange cost in dollars per flow from node i to node j, in network n [$\$/mile$]
cg	Average price for grid energy [$\$/kBtu$]
$cgeo$	Levelized cost for geothermal energy [$\$/kBtu$]
$csolar$	Levelized cost for solar energy [$\$/kBtu$]
$d_{i,j,n}$	Spatial Distance between nodes i and j, in network [$mile$]
$hd_{h,n}$	Energy demand of parcel h, in network n [$kBtu$]
$kc_{k,n}$	Energy supply for parcel k, in network n [$kBtu$]
$pArea_k$	Total building floor area of parcel k [m^2]
pct_t	Percentage of energy parcel's land use attributed to type t [%]
$pReqA_t$	Area required by land use type t [m^2]
rG	Electricity consumption rate (0.25) of a geothermal system
$u_{k,i}$	Adjacency matrix of source parcel k to supply node i
$v_{j,h}$	Adjacency matrix of demand node j to demand parcel h
w	Objective function weights
$ycn_{i,n}$	Cost for node i, in network n, to obtain supplemental energy from the grid [$\$/kBtu$]

Sets

I	Set of nodes $i, j \in I$
K	Set of urban parcels, $k, h \in H$
N	Set of energy exchange networks (1 = electrical, 2 = thermal)
T	Set of land use classes

Variables

$b_{k,n}$	Amount of geothermal installed at parcel k, in network n
$ks_{k,n}$	Energy supply used from parcel k, in network n [$kBtu$]
$p_{j,h,n}$	Energy flow among nodes j,h, in network n
$p_{k,i,n}$	Energy flow among nodes k,i, in network n
$x_{i,j,n}$	Energy flow from node i to node j, in network n
$y_{i,n}$	Energy required from the grid at node i, in network n
$yge_{k,n}$	Geothermal electricity energy consumption at parcel k, in network n
$ygh_{k,n}$	Geothermal heating energy supply at parcel k, in network n
$ypf_{k,t}$	parcel k with land use type t $\in \{0,1\}$

Objectives:

$$z_1 = \sum_{k\in K, t\in[3]} yp\,f_{k,t} * pArea_k$$
$$z_2 = \sum_{i\in I, j\in J, n\in N} x_{i,j,n}$$
$$z_3 = \sum_{i\in I, j\in J, n\in N} c_{i,j,n} * x_{i,j,n}$$

$$z_4 = \sum_{i\in I, n\in N} y_{i,n} * ycn_{i,n}$$
$$z_5 = \sum_{k\in K, n\in N} cg * yge_{k,n}$$
$$z_6 = \sum_{k\in K, n\in N} cgeo * ygh_{k,n}$$
$$z_7 = \sum_{k\in K, i\in I, n\in N} csolar * (p_{k,i,n} * u_{k,i,n} - ygh_{k,n} + yge_{k,n})$$

$$\max\ (w_1)z_1 + (w_2)z_2 - (w_3)z_3 - (w_4)z_4 - (w_5)z_5 - (w_6)z_6 - (w_7)z_7 \tag{1}$$

Constraints:

$$\sum_{t\in T} yp\,f_{k,t} = 1 \qquad \forall k \in K \tag{2}$$
$$\sum_{t\in T} (yp\,f_{k,t})(pReqA_t) \leq pArea_k \qquad \forall k \in K \tag{3}$$
$$\sum_{t\in T} (yp\,f_{k,t})(pArea_k) = pArea_k \qquad \forall k \in K \tag{4}$$
$$\sum_{k\in K} (yp\,f_{k,t})(pArea_k) / \sum_{k\in K} pArea_k \geq pct_t \qquad \forall t \in [0, 1, 2] \tag{5}$$
$$\sum_{i\in I} (p_{k,i,n})(u_{k,i}) = ks_{k,n} + ygh_{k,n} - yge_{k,n} \qquad \forall k\in K\ \forall n\in N \tag{6}$$
$$\sum_{j\in J} (p_{j,h,n})(v_{j,h}) = hd_{h,n} \qquad \forall h\in H\ \forall n\in N \tag{7}$$
$$\sum_{k\in K} (p_{k,i,n})(u_{k,i}) + y_{i,n} = \sum_{j\in J} x_{i,j,n} \qquad \forall i \in I\ \forall n \in N \tag{8}$$
$$\sum_{h\in H} (p_{j,h,n})(v_{j,h}) = \sum_{i\in I} x_{j,i,n} \qquad \forall j \in J\ \forall n \in N \tag{9}$$
$$ks_{k,n} \leq kc_{k,n} \qquad \forall k\in K\ \forall n\in N \tag{10}$$
$$ygh_{k,n} \leq (b_{k,n})(bt_{k,n}) \qquad \forall k\in K\ \forall n\in N \tag{11}$$
$$yge_{k,n} = (ygh_{k,n})(rG) \qquad \forall k\in K\ \forall n\in N \tag{12}$$
$$b_{k,n} \leq bM_{k,n} \qquad \forall k\in K\ \forall n\in N \tag{13}$$
$$p_{k,i,n},\ p_{j,h,n},\ x_{i,j,n},\ y_{i,n},\ ygh_{k,n},\ yge_{k,n},\ b_{k,n} \geq 0 \tag{14}$$

Equation (2) assigns a type, t, to each parcel, k. Equation (3) ensures that the total area of parcel k with type t is less than or equal to the regulated area allowed for this use-type, from an urban planning perspective ($pReqA_t$). Equation (4) ensures the total floor area of the assignments matches the input planning envelope design. Equation (5) ensures a certain percentage of the total urban area is assigned to each land use type, t. Equation (6) defines the energy supply available at each parcel, k, as what is available from solar absorption, $kc_{k,n}$ and installed geothermal, $ygh_{k,n}$, less the amount of electricity utilized by the geothermal heat pump (Equation (12)). Similarly, Equation (7) defines the electrical and heating demand at parcel h. Equation (8) ensures that the energy exchanged from node *i* is equal to the energy supply available. Equation (9) makes sure that the demand at each node, j, is satisfied. Equation (10) defines the input energy supply from solar resources. Equation (11) defines the geothermal heat supply available, which is constrained by the physical maximum geothermal supply of the parcel (Equation (13)). Non-negativity constraints for decision variables are satisfied in Equation (14).

To validate the effectiveness of a local energy exchange network, we compare the energy efficiency and renewable energy investments made with a network, to an urban plan without such a network. This results in a slightly different formulation of the optimization model, described below.

$hd_{k,n}$ Energy demand of parcel k, in network n without network connections [*kBtu*]
$ycn_{k,n}$ Cost for parcel k, in network n, to obtain supplemental energy from the grid [$\$/kBtu$]

$$ks_{k,n} + ygh_{k,n} - yge_{k,n} + y_{k,n} = hd_{k,n}, \ \forall k \in K \ \forall n \in N, \tag{15}$$

where

$ks_{k,n}$: solar supply for each parcel *k* and energy type (1 = electric, 2 = thermal) *n*
$ygh_{k,n}$: geothermal supply for each parcel *k* and energy type *n*
$yge_{k,n}$: geothermal consumption for each parcel *k* and energy type *n*
$y_{k,n}$: grid supply for each parcel *k* and energy type *n*
$hd_{k,n}$: energy demand for each parcel *k* by energy type *n*

In a model without a local energy network, Equation (15) replaces Equations (6) - (9). An additional change is that z2 and z3 are dropped from the original multi-objective function, as the network has been eliminated. Such a version of the optimization model takes as input the same parameters as the networked version, but results in different decisions for renewable energy investment and overall urban energy efficiency, as discussed in Section 3.

3 RESULTS AND DISCUSSION

More than 5,000 EPNs were generated from the first step of the Infomorphism framework (see Section 2.1 for a detailed description of the generation process); each EPN was then run through the energy network optimization model described in Section 2.2; each optimization process took approximately 15 seconds to complete. Overall, the EPNs with high renewable integration rates contain tall, but thin, EPs which negotiate the form of their envelope based on the objective function z1 to z7 defined in the optimization model. The less energy efficient EPNs are low and flat shaped EPs, which were developed based on current planning regulations (See Figure 1).

Results with local energy networks show that energy networks always enable a lower total cost because the EPNs require less geothermal energy installation, due to the energy available via the exchange network.

Figure 1: Left: Heat map of Low-Performance EPN with demand; Right: Heat map of High-Performance EPN with demand; red in the heat map indicates high energy demand while blue denotes low energy demand

Results without a local energy network demonstrated a higher total energy cost because almost every EP required installing geothermal systems in order to close the gap between supply and demand. As validation of this finding, we created an EPN with an overwhelming solar energy potential, larger than the demand. In this extreme case, no EP needed to install geothermal systems when a local energy exchange network was present, as the network could provide an optimal energy exchange to balance supply and demand efficiently. On the contrary, in the "no-network" scenario, the optimized investment decision required 45 geothermal heat pumps, as well as extra energy from the grid.

Table 1: Comparison of Optimization Results for 4 Representative EPNs

Name	**Low-PERF EPN**	**Low-PERF EPN**	**High-PERF EPN**	**High-PERF EPN**
Scenario	w/o Networks	w/ Networks	w/o Networks	w/ Networks
Total Energy Demand [kBtu]	2.79×10^{9}	2.79×10^{9}	2.06×10^{9}	2.06×10^{9}
Node to Node Energy Flow [kBtu]	0	2.79×10^{9}	0	2.06×10^{9}
Local Energy Network [No. connections]	0	209	0	214
Demand Unmet by Solar [kBtu]	2.40×10^{9}	2.40×10^{9}	1.32×10^{9}	1.32×10^{9}
Solar Percentage	14.00%	0.141	0.357	0.36
Geothermal Percentage	51.30%	0.511	0.38	0.38
Grid Percentage	34.70%	0.348	0.263	0.26
Total Weighted Energy Cost [$]	7.16×10^{7}	6.98×10^{7}	4.76×10^{7}	4.54×10^{7}
Un-Used Solar Energy [kBtu]	3.25×10^{4}	0	4.68×10^{6}	0
Geothermal Installation [No. units]	119	57	118	49

For both scenarios with and without a local energy exchange network, since the levelized cost for geothermal ($0.010 per kBtu) and solar ($0.012 per kBtu) is lower than the levelized grid energy price ($0.305 per kBtu), investments in geothermal and solar energy were prioritized over purchases from the grid. However, if the grid energy cost is reduced to $0.020 per kBtu or lower, the optimization model prioritizes energy from the grid over geothermal energy, in order to minimize the total system cost. In general, strategies of assigning weighted costs to energy resources affect the optimal results; thus, the exploration of the model's sensitivity to costs helps to develop detailed plans for efficiently using renewable energy.

Table 1 indicates a significant difference of Total Weighted Energy Cost (TWEC) between neighborhoods whose buildings are connected with a local energy exchange network and neighborhoods whose buildings are not. For example, for both scenarios presented in the table, there is an approximate 3.5-5% of TWEC increase when buildings in a neighborhood are responsible only for their own energy. In other words, we have found that a collection of unconnected ZEBs is a less efficient way to integrate local renewable energy within a neighborhood. Our preliminary results indicate that higher efficiency can be achieved if we aim for a Zero Energy Neighborhood (ZEN) - with input from the central grid until the levelized cost of solar and geothermal becomes less than that of the central grid.

Some low energy performance EPNs might become more energy efficient if renewable energy could be exchanged from one to the other. Review of all the results with the local energy exchange network reveals that the high-performance EPN requires more energy exchange connections; however, it requires fewer geothermal installations compared to the low-performance EPNs. In a general planning process, the optimization model provides a way to analyze the difference between fundamental urban energy systems in terms of renewable energy integration. Because EPNs are generated based on planning regulations, the model can also evaluate relationships between specific regulations and the overall energy efficiency of a city.

Results of this modeling and simulation effort are not absolute numbers recommending specific actions or envelope designs of a city (see Table 1). Rather, the Infomorphism framework allows users to evaluate system design approaches and urban policies in relationship to renewable energy integration. As a general planning process, these results help urban designers and planners to understand and compare the trade- offs among different renewable energy resources and different local energy network designs. Synthesizing these results can inform improvement of the current regulations to increase urban energy efficiency via local energy networks, and can even inform policies related to energy justice, ensuring equitable renewable energy access to all inhabitants of a future city.

Many challenges exist for an energy-based urban planning framework, which constitute opportunities for further work. The first challenge is data availability of energy demand at a more granular level, as current data is aggregated annually. Higher resolution of energy demand data, ideally hourly, would allow higher fidelity and more accurately represent supply and demand exchanges. Furthermore, an energy demand prediction model that could be generalized and accurately utilized at any location would be a highly valuable advance. The second major challenge is in optimizing the integration strategy for the sub-modules of the current framework: the parametric model, simulation model, and network optimization model. Each relies on input from the other, but currently only via a limited set of parameters. Further integration into a single module would speed processing times and efficiency of the overall framework. Development of additional sub-modules could further integrate the aspects of energy envelope variability and energy supply calculation more efficiently.

4 CONCLUSIONS

Unlike the way in which cities have traditionally been designed with buildings laying on top of a centralized infrastructure grid, a future city, which contains an organized collection of ZEBs forms a decentralized, agent-based urban environment. To plan this type of city, considering the interactions between different neighborhoods, the proposed Infomorphism framework integrates a generative planning model with a data-driven, bottom-up UBEM process. The developed optimization model helps to optimize EPNs from both the urban planning design and engineering perspectives. In our case, energy supply and demand of each energy parcel is optimized through both the configuration of each EP and a local energy network. As a result, the framework recommends an optimal EPN from generated data, as well as a set of optimal local energy networks. High-Performance EPNs allow a future city to be powered by up to 74% renewable energy if the environment contains only ZEBs. The exploration between urban morphology and renewable energy penetration helps to understand the impact of renewable energy integration on future city plans, as well as informs urban policies for integrating local energy networks with the central grid.

Current work extends this optimization framework to a Deep Reinforcement Learning environment (Arwa and Folly 2020), so that the framework can not only deal with more complex negotiations between urban morphology and network design, but also recommend optimal solutions without the computational burden of running the optimization model for every dataset, as was done in this study over 4,000 times. To improve the framework's capacity of handling more complex planning problems, we will not only generate EPs based on the current planning regulations in Manhattan, but also simulate possible future planning regulations, such as land use, type of the parcel, or Floor Area Ratio (FAR), to explore a wider variety of strategies for planning a future city.

REFERENCES

Ali, U., M. H. Shamsi, C. Hoare, E. Mangina, and J. O'Donnell. 2021. "Review of Urban Building En- ergy Modeling (Ubem) Approaches, Methods and Tools Using Qualitative and Quantitative Analysis.". *Energy and Buildings* vol. 246, pp. 111073.

Arwa, E. O., and K. A. Folly. 2020. "Reinforcement Learning Techniques for Optimal Power Control in Grid-Connected Microgrids: A Comprehensive Review.". *IEEE Access* vol. 8, pp. 208992–9007.

Barone, G., A. Zacharopoulos, A. Buonomano, C. Forzano, G. F. Giuzio, J. Mondol, A. Palombo, A. Pugsley, and M. Smyth. 2022. "Concentrating Photovoltaic Glazing (CoPVG) System: Modelling and Simulation of Smart Building Façade.". *Energy* vol. 238, pp. 121597.

Buker, M. S., and S. B. Riffat. 2015. "Building Integrated Solar Thermal Collectors – a Review.". *Renewable and Sustainable Energy Reviews* vol. 51, pp. 327–46.

Bynum, M. L., G. A. Hackebeil, W. E. Hart, C. D. Laird, B. L. Nicholson, J. D. Siirola, J.-P. Watson, and

D. L. Woodruff. 2021. Pyomo–optimization modeling in python. Third ed, Volume 67. Springer Science & Business Media.

Chen, Y., T. Hong, and M. A. Piette. 2017. "Automatic Generation and Simulation of Urban Building Energy Models Based on City Datasets for City-Scale Building Retrofit Analysis.". *Applied Energy* vol. 205, pp. 323–35.

Crawley, D. B., C. O. Pedersen, L. K. Lawrie, and F. C. Winkelmann. 2000. "EnergyPlus: Energy Simulation Program". *ASHRAE Journal* vol. 42, pp. 49–56.

Derkenbaeva, E., S. H. Vega, G. J. Hofstede, and E. van Leeuwen. 2022. "Positive energy districts: Mainstreaming energy transition in urban areas". *Renewable and Sustainable Energy Reviews* vol. 153, pp. 111782.

Durga, S., K. F. Beckers, M. Taam, F. Horowitz, L. M. Cathles, and J. W. Tester. 2021. "Techno-Economic Analysis of Decarbonizing Building Heating in Upstate New York Using Seasonal Borehole Thermal Energy Storage.". *Energy and Buildings* vol. 241, pp. 110890.

Ferrando, M., F. Causone, T. Hong, and Y. Chen. 2020. "Urban Building Energy Modeling (UBEM) Tools: A State-of-the-Art Review of Bottom-up Physics-Based Approaches.". *Sustainable Cities and Society* vol. 62, pp. 102408.

Kontar, R. E., B. Polly, T. Charan, K. Fleming, N. Moore, N. Long, and D. Goldwasser. 2020. "URBANopt: An Open-Source Software Development Kit for Community and Urban District Energy Modeling". In IBPSA Building Simulation Conference. Preprint. Golden, CO: National Renewable Energy Laboratory. NREL/CP-5500-76781.

Kosicki, M., M. Tsiliakos, and M. Tsigkari. 2019. "Hydra Distributed Multi-Objective Optimization for Designers.". In Impact: Design With All Senses, pp. 106–18.

Lasseter, R. H., and P. n. Paigi. 2004. "Microgrid: A conceptual solution.". In IEEE 35th Annual Power Electronics Specialists Conference (IEEE Cat. No.04CH37551).

Li, H., T. Hong, and W. Zhang. 2021, November. "Modelling and Simulation of District Heating and Cooling Systems Using CityBES.". In IBPSA Building Simulation Conference.

Liu, X., and Y. Wu. 2021. "Design, Development and Characterisation of a Building Integrated Concentrating Photovoltaic (BICPV) Smart Window System.". *Solar Energy* vol. 220, pp. 722–34.

Makhorin, A. 2020. "GLPK (GNU Linear Programming Kit)".

McNeel, R., and others 2022. "Rhinoceros Grasshopper". *Robert McNeel Associates*. Seattle, WA.

Nagy, D., L. Villaggi, and D. Benjamin. 2018. "Generative Urban Design: Integrating Financial and Energy Goals for Automated Neighborhood Layout.". In SimAUD 2018 Conference Proceedings.

Nian, Y.-L., and W.-L. Cheng. 2018. "Evaluation of Geothermal Heating from Abandoned Oil Wells.".

Energy vol. 142, pp. 592–607.

Niu, J., Z. Tian, Y. Lu, and H. Zhao. 2019. "Flexible Dispatch of a Building Energy System Using Building Thermal Storage and Battery Energy Storage.". *Applied Energy* vol. 243, pp. 274–87.

Novelli, N., K. Phillips, J. Shultz, M. M. Derby, R. Salvas, J. Craft, P. Stark, M. Jensen, S. Derby, and

A. Dyson. 2021. "Experimental Investigation of a Building-Integrated, Transparent, Concentrating Photovoltaic and Thermal Collector.". *Renewable Energy* vol. 176, pp. 617–34.

NYC Department of City Planning, PLUTO21v3. "The Primary Land Use Tax Lot Output (PLUTO™) data 2021".

NYC Office of Climate & Sustainability, Green Building & Energy Efficiency. "Energy and Water Data Disclosure for Local Law 84 2021 (Data for Calendar Year 2020)".

Roudsari, S., and M. S. Roudsari. 2013, August. "Ladybug: a parametric environmental plugin for grasshopper to help designers create an environmentally-conscious design.". In In: Proceedings of the 13th International IBPSA Conference. Lyon, France.

Setlhaolo, D., S. Sichilalu, and J. Zhang. 2017. "Residential Load Management in an Energy Hub with Heat Pump Water Heater.". *Applied Energy* vol. 208, pp. 551–60.

Shi, Z., J. A. Fonseca, and A. Schlueter. 2017. "A Review of Simulation-Based Urban Form Generation and Optimization for Energy-Driven Urban Design.". *Building and Environment* vol. 121, pp. 119–29.

Singh, V., and N. Gu. 2012. "Towards an Integrated Generative Design Framework.". Design Studies vol.

33, pp. 185–207.

Soltani, M., F. M. Kashkooli, A. Dehghani-Sanij, N. B. A.R. Kazemi, M. Farshchi, K. G. M. Elmi, and M. B. Dusseault. 2019. "A Comprehensive Study of Geothermal Heating and Cooling Systems.". *Sustainable Cities and Society* vol. 44, pp. 793–818.

Strasser, T., F. Andrén, J. Kathan, C. Cecati, C. Buccella, P. Siano, P. Leitão, G. Zhabelova, V. Vyatkin,

P. Vrba, and V. Maˇrík. 2015. "A Review of Architectures and Concepts for Intelligence in Future Electric Energy Systems". *IEEE Transactions on Industrial Electronics* vol. 62 (4), pp. 2424–2438.

Touzani, S., J. Granderson, and S. Fernandes. 2018. "Gradient Boosting Machine for Modeling the Energy Consumption of Commercial Buildings.". *Energy and Buildings* vol. 158, pp. 1533–43.

Tsamis, A., Y. Hwang, and T. Borca-Tasciuc. 2020. "An Ectothermic Approach to Heating and Cooling in Buildings". In 2020 AIA/ACSA Intersections Research Conference: CARBON.

United States. U.S. Energy Information Administration EIA, EIA01. "Levelized Costs of New Generation Resources in the Annual Energy Outlook 2021".

Van Rossum, G., and F. L. Drake Jr. 1995. Python reference manual. Centrum voor Wiskunde en Informatica Amsterdam.

Wilson, L., J. Danforth, C. C. Davila, and D. Harvey. 2019, April. "How to Generate a Thousand Master Plans: A Framework for Computational Urban Design.". SimAUD 2019.

Xu, S., C. Yan, and C. Jin. 2019. "Design Optimization of Hybrid Renewable Energy Systems for Sustainable Building Development Based on Energy-Hub.". *Energy Procedia* vol. 158, pp. 1015–20.

AUTHOR BIOGRAPHIES

FENGQI LI is a PhD Candidate at the Center for Architecture Science and Ecology at Rensselaer Polytechnic Institute. His email address is lif4@rpi.com.

ALEXANDROS TSAMIS is an Architect and Assistant Professor at the school of architecture, Rensselaer Polytechnic Institute. His email address is tsamia@rpi.edu.

KRISTEN SCHELL is an Assistant Professor in Mechanical and Aerospace Engineering at Carleton University. Her email address is kristenschell@cunet.carleton.ca.