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Dynamic shifts in building energy demand: an activity-based analysis of post-COVID work and lifestyle changes

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Abstract. During and after the COVID-19 pandemic, significant changes occurred in lifestyles of residents worldwide. This study aims to develop an activity-based urban energy modelling framework to capture the impact of changes in urban residents' activity time and location choices on cross-sectoral urban energy demand. The framework employs a utility-based model to characterise the spatiotemporal patterns of urban population activity choices and derives the temporal and spatial variations in energy demand. The model was validated using data from the Guangzhou Resident Lifestyle Survey (GRLS). In addition, this study examines a typical local neighbourhood as a case study, calculating changes in building energy demand resulting from the promotion of home-based, hybrid, and multi-locational working arrangements through scenario settings. Research findings indicate that flexible working arrangements shift daytime energy demand on workdays from office buildings to residential buildings, with this shift also influenced by external climatic factors such as temperature and weather conditions. This study provides a novel activity-based perspective for urban energy management, enabling scholars to gain insights into energy demand trends arising from emerging changes in residents' activity patterns in fast-growing cities. These insights will assist urban policymakers in formulating cross-sectoral energy strategies and planning measures to enhance community and urban energy resilience.

1. Introduction

The spatial and temporal distribution of human activities fundamentally shapes urban energy systems. As individuals navigate through their daily routines, moving between residences, workplaces, and leisure venues. They create activity chains that generate distinctive patterns of energy consumption across multiple building sectors. These activity chains represent the sequential engagement in various pursuits, each with its own locational, durational, and intensity characteristics that directly influence energy demand profiles [1], [2]. Especially, these patterns are not static: they respond dynamically to socioeconomic, technological, and environmental changes that alter how activities are conducted [3].

In the past decades, the urban population has witnessed unprecedented shifts in established activity patterns. After the COVID-19 pandemic, the emerging working pattern changes play a critical role in such a process [4], [5]. The new productivities and remote collaboration tools enable novel working patterns such as home-based work, hybrid workings, and decentralised office utilisation [6]. While initially accelerated by the pandemic and associated mobility restrictions [6], [7], the transformations have crystallised into enduring structural changes across countries [8]. Post-pandemic assessments indicate that new working patterns have become embedded in organisational practices [6], [8], [9].

These emerging working patterns have profound implications for cross-sectoral energy flows [2], [10]. When activities shift spatially, for instance, from commercial offices to residential settings, they create corresponding shifts in energy consumption profiles across building sectors [11]. For example, homeworking may reduce demand in commercial buildings whilst simultaneously increasing residential consumption [12], thus creating a complex redistribution rather than a simple reduction or increase in aggregate demand [13]. This energy demand flow across sectors presents new challenges for energy systems planning and carbon reduction strategies. Despite the significance of these interconnections, current energy modelling approaches often treat building sectors as discrete entities, failing to capture the dynamic flows driven by human activity chains [14].

Traditional city-scale energy analysis has typically emphasised single functional sectors. Following the foundational work of Hägerstrand's [15] on time geography, researchers have increasingly recognised the importance of individual activity patterns in shaping urban and regional dynamics [16], [17]. However, existing research has insufficiently addressed how different working patterns influence activity chains and derived cross-sectoral energy demand change. This paper aims to bridge this gap by proposing a utility-maximising modelling framework that captures the heterogeneity of individual activity patterns under different working patterns: specifically comparing homeworkers, commuters, hybrid workers, and multi-workplace workers. Utilising data collected in Guangzhou, China, this study examines how various working patterns influence broader activity decisions among residents with diverse sociodemographic characteristics. Building upon these analytical findings, we employ a local community as a case study for energy modelling. The study then evaluates working pattern-based scenarios to assess potential impacts on residential and office sectoral energy demands.

The research offers several unique contributions: (1) it conceptualises energy demand not as sector-bound but as activity-driven and spatially mobile across building types. (2) it provides a framework for quantifying how working pattern shifts cascade through activity chains to redistribute energy demand and offering insights for energy interventions. The findings have significant implications for urban policies aimed at reducing environmental impacts and promoting cross-sectoral energy management.

2. Methods and Data

2.1. Modelling Method Overview

Figure 1 illustrates the theoretical framework underpinning our modelling approach, which builds upon the Wang and Wan's concept [2]. The framework consists of four interconnected components. The first component captures the constraints that influence activity demand patterns (e.g., new trends of working patterns). The second component then generates residents' activity demands accordingly. In the third component, these demands are allocated across different sectors. The fourth component examines how these demands affect sectoral performance and energy requirements, which could in turn modify social and environmental conditions, potentially triggering further changes in residents' activity demands.

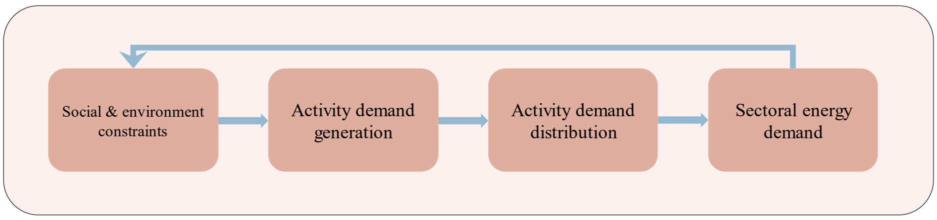

Figure 1. The Theoretical Framework

This research presents a case study focusing on Guangzhou, China during the COVID-19 pandemic. Following the theoretical framework outlined above, we first collect time use diaries of local employed residents to identify typical working patterns. The study then develops a utility-maximising model to simulate changes in activity demands under different working patterns. Subsequently, we employ an energy modelling case study of a representative local community to capture the energy implications of these activity pattern shifts. This approach generates occupancy schedules for both residential and office buildings based on the endogenous activity patterns, enabling to quantify the energy impacts of working pattern changes across residential and office buildings. This methodology allows for a comprehensive assessment of cross-sectoral energy flows resulting from new working patterns.

2.2. Time Use Survey Data Processing and Working Pattern Identification

This study employs time-use data from the Guangzhou Resident Lifestyle Survey (GRLS), which forms part of the broader Greater Bay Area (GBA) Resident Lifestyle Survey. Guangzhou, as one of the most significant cities in China's Greater Bay Area, is renowned for its trade and service industries. The GRLS was conducted during autumn 2021, collecting 30-minute interval activity records throughout workdays from 205 urban residents. Participants were required to meet two key criteria: (1) being currently employed, and (2) having resided in the city for more than three months (thus excluding temporary visitors). At the time of data collection, Guangzhou had already experienced its first wave of virus outbreak. By this point, the city had lifted strict social distancing restrictions.

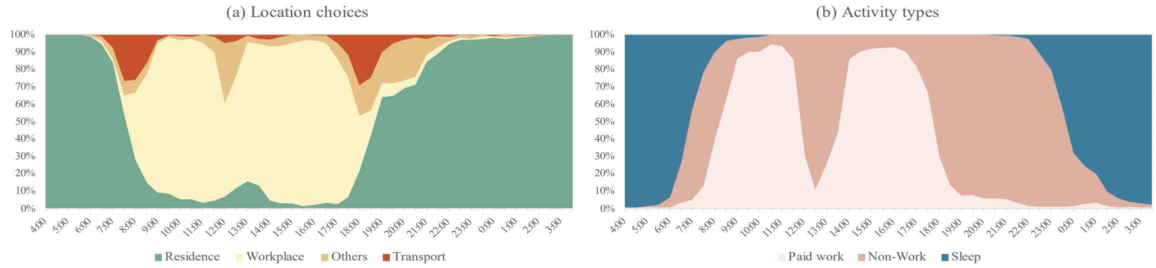

Figure 2. Overall time allocation patterns of the respondents

The survey recorded both activity type and location at each time interval. To facilitate our approach, we reclassified these data according to the research objectives: activity types were consolidated into three categories (paid work, non-work activities, and sleep), while locations were grouped into four categories (residences, workplaces, other fixed locations, and transport). Figure 2 illustrates the time-use characteristics reported by respondents across both activity type and location choice dimensions. For the respondents, the average time allocated for paid-work, non-work, and sleep are 468.44 minutes, 543.80 minutes, and 427.76 minutes respectively. The average time at residences, workplaces, others, and transport means are 770.20 minutes, 516.44 minutes, 93.07 minutes and 60.29 minutes.

Table 1. Comparison of the four working patterns

Working Pattern	Number (%)	Residence (unit: minute)	Workplace (unit: minute)	Others (unit: minute)	Transport (unit: minute)
Home-based	4 (1.95%)	1102.5	0	262.5	75
Commuting	149 (72.68%)	751.0	547.7	83.4	58.0
Hybrid	24 (11.71%)	796.3	515.0	66.3	62.5
Multi-location	28 (13.66%)	802.5	425.4	143.6	68.6

We classified respondents into four distinct working patterns based on their locational preferences for paid work activities: (1) Home-based working; (2) Commuting; (3) Hybrid working; and (4) Multi-locational working. Residents adopting the first pattern conducted all their paid work activities within residential settings. In contrast, those following the second pattern allocated all their work time to dedicated workplaces. Under the third pattern, hybrid workers distributed their working hours between residences and workplaces. The fourth pattern, multi-locational working, extended beyond these two locations, enabling residents to conduct work-related activities in other places as well. Table 1 presents the distribution of respondents across these four patterns and their characteristic time-use profiles.

2.3. Activity Modelling

The study employs the Multiple Discrete Continuous Extreme Value (MDCEV) model developed by Bhat et al. [18] for activity modelling, which has been applied to model budget-constrained activity time-use decisions over the past decade [5], [19]. The MDCEV structure surpasses conventional discrete choice models by simultaneously accommodating both discrete (e.g., activity type) and continuous (e.g., duration) decisions under resource constraints. Our activity model is built on random utility maximisation theory that assumes that individuals make their time allocation decisions to maximise the utility derived from their chosen activity patterns, subject to a time budget constraint (i.e., 24 hours). We identify sleep as an essential Hicksian composite (outside) good. Function (1) shows the MDCEV utility function for a time allocation choice $\boldsymbol{\mathcal{X}}$ in K alternative activities:

$$U(\boldsymbol{\mathcal{X}}) = \frac{1}{\alpha}\psi_1 x_1 + \sum_{k=2}^{K} \frac{\gamma_k}{\alpha}\psi_k \left\{(\frac{x_k}{\gamma_k}+1)^{\alpha_k} - 1\right\} \qquad \text{subject to } \sum_{k=1}^{K} x_k = T \qquad (1)$$

In equation (1), $U(\boldsymbol{\mathcal{X}})$ is a quasi-concave, increasing, and continuously differentiable function. $\boldsymbol{x}$ is a (K × 1) vector of time allocation to activity 1, 2, …. K ($x_k \geq 0$, for all k). To make the utility function valid, the parameter α should no more than 1, $\psi_1$and ψ_k > 0. ψ_k represents the marginal utility of time allocated to activity k. α and γ_k represent satiation parameters to provide a satiation effect. In our case, α is not associated with activity k. γ_k enables the corner solutions. T is the time budget. The model considers z_k as a set of attributes to represent the characteristics of activity k, and ε_k represents unobserved characteristics that impact the baseline utility. The model parameterised ψ_k as exp $(\beta' z_k)$, $\psi(x_1, \varepsilon_1) = \exp(\varepsilon_1)$, $\psi(x_k, \varepsilon_k) = \exp\,(\beta' z_k + \varepsilon_k)$. We use the package Apollo [20] for modelling.

2.4. *Building Energy Modelling*

Our case study utilises a typical *Danwei community* located in Guangzhou, China, to understand the energy implications of emerging work patterns among residents. *Danwei community* is a community type encompasses both enterprise office buildings and staff accommodation. The specific case includes three office buildings of varying heights: a 10-storey building (total area 4,583.646 sqm), a 6-storey building (total area 2,916.86 sqm), and a 3-storey building (total area 1,666.78 sqm). Also, it contains five 8-storey residential staff quarters (each with an area of 1,739.30 sqm), comprising 16 residential units per building. In our model configuration, the office buildings are assigned maximum occupant densities of 0.033 persons per sqm for public areas and 0.125 persons per sqm for office areas. We assume each residential unit houses three employed occupants. The climate characteristics are derived from local *Typical Meteorological Year* data. The activity model generates the occupancy schedules for each building based on the simulated location choice patterns. EnergyPlus v9.5 is employed for analysis.

3. Model Validation and Scenario Analysis

3.1. *Activity Model Validation*

This study randomly selected data from 75% of the sample for model calibration, with the remaining 25% used for validation. Figure 3 compares the observed time-use against those estimated by our model. Each point represents time allocation for different activities across various time periods. The coefficient of determination (R-squared) is 0.9876, demonstrating satisfactory predictive capability of the model. Table 2 further illustrates time allocation across residence (active/inactive), workplace, transport and other locations. Sleep (the outside good) was not included in Figure 3, but its data are listed in Table 2.

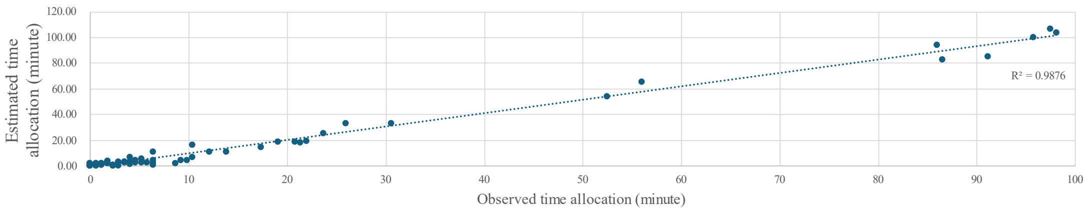

Figure 3. The validation results of activity modelling

Table 2. Aggregated time allocation by location (unit: minute)

	Residence	Workplace	Others	Transport	Sleep (outside)
Observed	351.35	503.65	112.50	68.08	404.42
Estimated	364.07	512.57	96.92	58.28	408.16
Diff. (%)	3.62%	1.77%	-13.85%	-14.39%	0.92%

3.2. Scenario Analysis

To understand the impacts of three working patterns, we established scenarios to examine the resulting residential and office occupancy patterns and their derived energy demands. The first two scenarios (S1A and S1B) focus on home-based working, scenarios S2A and S2B address hybrid working, whilst the final two explore multi-locational working. Table 3 provides detailed information on the settings of these scenarios. Within these scenarios, an increase in the number of employed residents engaged in new working patterns corresponds to a proportional decrease in traditional commuters.

Table 3. Scenario settings

Dimension		Home-based		Hybrid		Multi-location	
Scenario	Baseline	S1A	S1B	S2A	S2B	S3A	S3B
Change	N/A	+15%	+25%	+15%	+25%	+15%	+25%
Commuting%	72.68%	57.68%	47.68%	57.68%	47.68%	57.68%	47.68%
Home-based%	1.95%	16.95%	26.95%	1.95%	1.95%	1.95%	1.95%
Hybrid%	11.71%	11.71%	11.71%	26.71%	36.71%	11.71%	11.71%
Multi-loc.%	13.66%	13.66%	13.66%	13.66%	13.66%	28.66%	38.66%

3.2.1. Location Choices

We generate occupancy schedules for residential and office buildings based on the time-use patterns of employed populations derived from our activity model. Figure 4 illustrates these results, with Figures 4(a), (b) and (c) displaying the residential building (active), the residential building (including sleep), and the office building occupancy schedule, respectively. Compared to the baseline, all scenarios demonstrated longer residential active occupancy. Especially, S1A and S1B, associated with home-based working, increase active residential occupancy by 9.12% and 22.57%. These increases were concentrated between 10AM and 4PM. Also, S3A and S3B revealed that elevated multi-locational working ratios resulted in active residential occupancy increases of 3.22% and 6.02%. Home-based working similarly emerged as the working pattern with the most significant influence on office building occupancy, with effects generally inverse to the trends observed in residential occupancy.

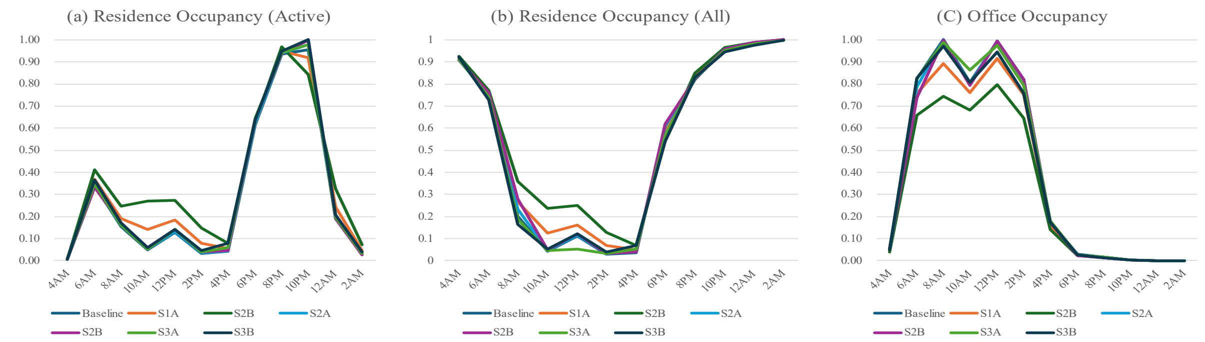

Figure 4. Generated residential and office building occupancy

3.2.2. Building Energy Demand

Figure 5 illustrates the energy demand changes in office buildings, residential buildings, and total energy requirements across the case study community. Results indicate that home-based working demonstrates a significant effect in reducing overall energy demand within this community: scenarios S1A and S1B yield electricity demand savings of 18.25 and 47.42 MWh respectively. Whilst home-based working may cause a slight increase in residential sector energy demand, the energy conservation effect in office buildings is more pronounced, reaching 11.36% in scenario S1B, resulting in an overall reduction in energy demand. The impact of home-based working on office energy demand exhibits seasonal variation, with energy-saving effects of 14.95% and 16.03% during the cooler months of January and February, compared to approximately 9% during the hot summer months (June-August). This discrepancy may be attributed to larger and more dispersed cooling requirements resulting from home working arrangements.

The scenarios focused on hybrid working demonstrate energy impacts similar in trend to S1A/S1B across both building types, albeit with more moderate effects (S2B achieving total savings of 3.91 MWh).

Figure 5. Building energy demand by scenario

4. Implications, Limitations and Future Directions

The significant shifts in building occupancy patterns resulting from emerging working arrangements necessitate proactive policy responses from urban planners and energy providers. Policymakers should monitor the evolving work pattern trends to accurately forecast building energy demand distributions. The transfer of daytime energy demand from office to residential areas may require reconfiguration of electricity grids to address increased residential daytime loads and prevent potential network stress.

Our findings indicate that home-based working produces the most dramatic shifts in energy demand patterns, whilst hybrid and multi-locational working create more moderate but complex energy distribution challenges requiring more nuanced management approaches. Multi-locational working particularly warrants attention as it may create scattered energy demand across various urban locations, potentially straining local infrastructure in previously low-demand areas. In the future, solutions could include time-of-use electricity pricing structures for remote workers, and neighbourhood-level energy-sharing schemes. In addition, urban planners might consider establishing local co-working hubs within residential areas to optimise energy distribution whilst maintaining the benefits of flexible working. Such strategic approaches would enhance urban energy resilience whilst supporting the sustainable transition to more flexible working patterns in post-pandemic urban environments.

Our data was collected during the COVID-19 pandemic, potentially not fully representing post-pandemic conditions. Also, the findings may be affected by the small sample size (205 respondents). Future research should incorporate activity chains to examine interactions among buildings, transport and facilities. Our case study assumed that the staff quarters contained only employed residents, neglecting the presence of non-employed residents. This simplification may not accurately reflect the complex inner household interactions. Furthermore, future studies would benefit from considering the complex activity-chain interaction between employed and non-employed residents.

Lastly, applying our findings in other regions requires a careful consideration of local building geometrical characteristics, climatic conditions, and work cultures. These factors can influence the relative prevalence of various working patterns as well as the energy performance of buildings. For example, while European cities are increasingly adopting a four-day working week, its adoption remains considerably lower in Asia. Also, in contrast to Asian metropolises, European cities typically exhibit a higher proportion of low-rise buildings. The influence of these variations could steer future localised energy retrofit [21] and city-level energy management.

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Declaration

Throughout the drafting of this paper, ChatGPT was utilised solely to enhance readability and linguistic clarity. The authors confirm that all outputs have been meticulously reviewed and edited, and maintains full accountability for the final content of the work.

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