Notes Paper: Intelligent network topology based post-pandemic reintroduction policies for offices

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ABSTRACT

COVID-19 has touched almost all facets of modern life. As part of this global shift, many employers have recommended employees work from home in an effort to curb the spread of infection. When organizations bring workers back to the office, the specific policies for personnel reintroduction will shape both productivity and the spread of disease. This study explores the secondary social and energy impacts of potential reintroduction policies. Using a socio-organizational network inferred from an office in Redwood City, California, we define social, epidemic resistance, and energy metrics which are used to compare the character of personnel reintroduction plans. Our notable findings are, first, that the choice of *which* occupants return has a large effect on modeled network-level epidemic resistance. Second, *where* the occupants are located can significantly impact overlap in space-use within smaller spatial zones – a concept related to social distancing. In summary, this work is a critical first step in demonstrating the value of intelligent occupant network topology based reintroduction schemes in offices that can minimize: disease spread, socio-organizational disruptions and building energy use impacts.

CCS CONCEPTS

• **Applied computing** → Sociology; *Architecture (buildings)*; • **Networks** → **Network dynamics**; • **Theory of computation** → **Dynamic graph algorithms**.

KEYWORDS

Socio-Spatial Resistance Optimization, Eigenvalue Decomposition, Energy Analysis

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1 INTRODUCTION

The COVID-19 pandemic has altered many facets of daily life, and in the building sector it has pushed many office workers into their homes for remote work. Public health officials have promoted tools such as social distancing, face masks, and shelter-in-place restrictions. While from a public health perspective these social tools have a clear and immediate benefit [10], the organizational value lost is not as obvious. By definition, offices serve people by providing valuable working spaces for organizations. These spaces can facilitate positive relationship generation [1, 3] and the development of intangible social dynamics which drive economic activity [9]. Likewise, recent advances in smart sensing systems have enabled research into nonlinear relationships between power consumption, use of space, and ultimately organizational behavior and social dynamics [6]. While this past work provides valuable information for operational resource management, we propose that it also has a direct role in the development of optimal personnel reintroduction policies. As an example of this, past work has shown that better understanding of socio-organizational (SO) networks can inform higher quality infection models in dense office spaces [5].

In this paper, we introduce intelligent occupant network topology based reintroduction policies for reintroducing building occupants through the lenses of epidemic spreading potential, social value retention, and energy consumption. We then contextualize these findings for optimal space management (i.e., occupant layouts). Our data is sourced from a 151-occupant test-bed in Redwood City, California, where occupants' use of space and SO network structure are inferred from ambient plug load energy sensors.

2 METHODOLOGY

Our methodology centers on analyzing the data of 151 occupants and their behavioral patterns inferred from plug load energy devices from a commercial building space in Redwood City, California. We first use these behavioral patterns to infer the SO network describing relationships between individuals. We then introduce policies for reintroducing occupants to the workspace through the lenses of epidemic spreading, social network strength, and building energy consumption. Finally, we leverage a *behavioral diversity* metric to minimize the spatio-temporal overlap in use of space among occupants reintroduced to the office.

2.1 Data Preprocessing and Occupant Network

We collected 15-min plug load energy data (**X**) using Zooz SmartPlugs connected to a Samsung SmartThings hub over the period from July 10, 2019 to February 29, 2020. The raw energy data was mapped to occupant *activity states* ($\mathbf{X} \mapsto \mathbf{S}$) using the Variational Bayesian Gaussian Mixture Model clustering methods from ref. [8]. These states correspond to low, medium, and high energy consumption at the workstation, which in previous work, we have shown to be useful in modeling occupancy levels. We then learn a graph $G = (V, \mathbf{A})$, where V is the set of nodes (occupants) and $\mathbf{A}$ is the graph adjacency matrix. We learn $\mathbf{A}$ by defining *opportunities for social interaction* among the building occupants, as described in ref. [7]. The intuition behind the graph learning approach is that any two occupants who drop to a low or medium energy state in the middle of the workday have likely stopped using the equipment at their workstation and therefore have the opportunity to interact with one another in the space of the building. Repeated instances of interaction opportunity are hypothesized to signal a socio-organizational relationship, which we have confirmed in previous work. Formally, we compute the Jaccard Similarity between vectors describing interaction opportunities and use these similarities to populate the adjacency matrix.

2.2 Network Analysis

In this subsection, we develop four policies for reintroducing building occupants: maximizing epidemic resistance (max $\Delta\lambda$), maximizing social strength, acquaintance immunization, and random immunization (described in the subsections below). We introduce three metrics for evaluating these policies: social strength, epidemic resistance and energy consumption, which we describe here:

- **Social:** We define the social metric as the global sum of edge weights in the graph:
$$\sum_i \sum_j \mathbf{A}_{ij} \tag{1}$$
- **Epidemic resistance:** Our resistance metric is defined as:
$$\frac{1}{\rho(\mathbf{A})} := \frac{1}{max\{|\lambda_1|, ..., |\lambda_n|\}} \tag{2}$$
Motivations for this metric can be found in the following subsection.
- **Energy:** This metric is the result of data-driven simulation of the building's lighting system using a random forest model from the literature. The energy simulation model relies on the spatial layout of occupants, standard time-series information, and the occupants' *activity states*. In general, once a lighting zone is occupied, the lighting fixtures in that zone turn on. (details in ref. [6])

Here we discuss the four reintroduction policies, each of which transitions the space from a fully unoccupied state to a fully occupied state. These two states serve as effective boundary conditions, and a transition plan from unoccupied to occupied constitutes a reintroduction policy. We define an approach for optimal epidemic resistance and social strength through the use of a greedy algorithm, which allows us to estimate the upper and lower bounds of potential transition policies between these two boundary states.

As each policy navigates between the same boundary states, the metrics can be normalized against the values obtained at the boundaries. This permits us to examine the area under each of the normalized policies for an approximation of the total metric value through the reintroduction process. Due to the definition of the resistance $1/\rho(\mathbf{A})$, it is the only metric that will achieve scores greater than one.

```
for i in G do
    for j in G do
        G′ ← G\{j};
        metric_list[i] ← objective_function(G′);
    end
    choice_node ← max(metric_list);
    G ← G\{choice_node};
end
```

Algorithm 1: Greedy Algorithm

2.2.1 Max-$\Delta\lambda$ Optimization. Epidemic threshold (τ) relates the birth rate (β) and death rate (γ) of the virus, such that if $\tau > \frac{\beta}{\gamma}$ the virus will rapidly die off. Epidemic spreading is thus both a function of the viral character (β, γ) and the network topology (τ), indicating that manipulation of the network's topology can be used to manage epidemic spreading.

Prior work shows that given a network defined by potential transmission paths between nodes, the spectral radius $\rho(\mathbf{A})$ of the respective adjacency matrix can be used for estimation of the network's epidemic threshold ($\tau \approx 1/\rho(\mathbf{A})$) [2]. To briefly summarize this prior work, the spectral radius is defined as the largest absolute value of the eigenvalues – $max\{|\lambda_1|, ..., |\lambda_n|\}$. This approximation is particularly powerful as it holds for arbitrary network topology [2], and thus can be extended to any transmission network regardless of topology. Further, this approximation has further been extended to weighted graphs like ours [4]. These same bodies of work propose that the ideal immunization policy is one which most aggressively reduces $\rho(\mathbf{A})$. Therefore the objective function for our greedy algorithm is designed to optimize $\rho(\mathbf{A})$. As such, optimal reduction of $\rho(\mathbf{A})$ characterizes the *High Resistance* policy. To reiterate, the normalized area of the resistance metric – defined as $1/\rho(\mathbf{A})$ – will therefore be defined as the inverse of this final unit area.

2.2.2 Social Optimization. The social optimization also uses the greedy algorithm for optimization where the objective function is defined as the sum of edge weights through the adjacency matrix (equation 1). Maximizing this function creates the *High Social* polic, whereas and minimizing it creates the *Low Social* policy.

2.2.3 Baselines: Acquaintance and Random immunization. The *Acquaintance* policy [4] does not use the greedy algorithm, but randomly selects a node and chooses to remove one of its neighbors. In this way, it it can capture local network topology and is more likely to identify central nodes. For our analysis, the neighbors were selected with probability weight equal to the edge weight between the nodes. Reversing this node removal process constitutes the node reintroduction process.

The *Random* policy simply chooses a random node in the network and reintroduces that occupant into the building. As these methods require no prior knowledge of the network, we utilize them as baseline policies.

2.3 Spatial Layout Optimization

Once a reintroduction policy is chosen, building managers may be concerned with finding the optimal policy for maintaining as much social distancing as possible. Previous work has leveraged Euclidean distance to describe differences in occupant use of space, with the resulting metric referred to as *behavioral diversity* in occupant schedules [6]. Using the occupant schedule data S, we can define the distance between two occupants i and j as:

$$d_{i,j} = \sqrt{\sum_{t=0}^{T} \left(\mathrm{S}_{i,t} - \mathrm{S}_{j,t}\right)^2} \tag{3}$$

for any time range $0, ..., T$. Using this distance metric, we can compute the distances between all occupants in a space to form a distance matrix.

Previous work [6] has indicated that minimizing this zone-level behavioral diversity metric by rearranging occupants across the building zones can reduce the energy consumption of building systems (e.g., lighting, HVAC). This perspective can be viewed as "aligning" occupant behavior across space and time. If, however, we are interested in "misaligning" occupant behavioral patterns to reduce the chances that occupants simultaneously share the same spaces, we can flip the optimization function and attempt to maximize zone-level behavioral diversity. Our approach for maximizing behavioral diversity follows the clustering optimization introduced in [6]. We first choose an occupant at random. We then simulate the effect on zone-level behavioral diversity of swapping that occupant with all other occupants in the building. We execute the spatial swap that *maximizes* behavioral diversity and repeat this process until an iteration limit is reached.

Once occupants are rearranged in space, we can also re-simulate the energy consumption of the lighting system using the random forest model discussed previously and introduced in ref. [6].

3 RESULTS

3.1 Network Metrics

Fig. 1 demonstrates the evolution of the resistance metric as occupants are reintroduced under the *High Resistance* and *Low Resistance* policies. The *resistance score* is the inverse of the area, thus it achieves a score of 3.97 in this example. The *Low Resistance* policy would score much lower in this metric, in our example the inverse of the area is only 1.34.

Table 1 shows the overall social, resistance, and energy scores (area under the curve) for each office reintroduction policy in our case study. Comparing the two stochastic policies – *Random* and *Acquaintance* – it becomes clear that the *Acquaintance* based immunization policy provides greater network resistance and is recommended when there is no prior information about the network.

3.2 Spatial Layout Analysis

We chose the *High Social* scenario for further analysis as such a scenario minimizes socio-organizational disruptions that can impact productivity. Fig. 2 shows the evolution of the occupant behavioral diversity metric as occupants are reintroduced under this policy. This figure shows the behavioral diversity metric for both the existing layout where occupants return to their original seats and the

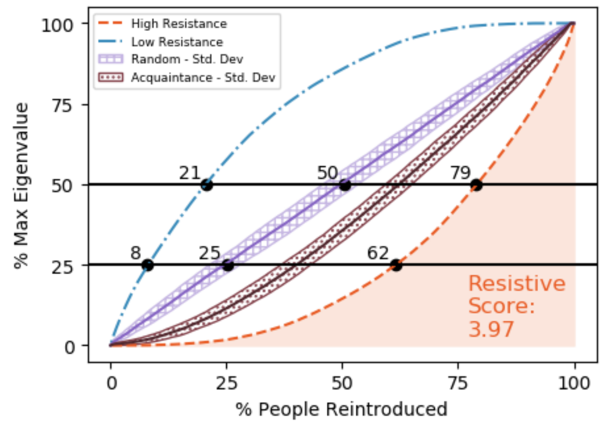

Figure 1: Evolution of the resistance metric as occupants are reintroduced under various policies. Area for the *High Resistance* policy is shown as an example.

Table 1: Social Reintroduction Analysis

	Social	Resistance	Energy
High Social	0.530	1.344	0.196
Low Social	0.202	3.968	0.157
High Resistance	0.202	3.968	0.157
Low Resistance	0.530	1.344	0.196
Acquaintance	0.212	3.322	0.133
Random	0.256	2.645	0.139

seating layout with an optimal behavioral diversity metric. When 50% of the occupants are reintroduced to the building, the behavioral diversity metric can be increased by 38%. This rearrangement of the space has a minimal impact on energy consumption (increase of 1%). For context, if one were interested in minimizing the behavioral diversity metric and aligning occupant behavior in time and space, the behavioral diversity metric can be reduced by 37% with a resulting decrease in energy consumption of 7%.

4 DISCUSSION AND CONCLUSION

Overall, our results indicate the potential of utilizing a data-driven approach for occupant reintroduction into shared office spaces. As seen in fig.1, if an office manager deemed that 25% of the original $\rho(\mathbf{A})$ was an appropriate threshold for safe reintroduction, they could reintroduce 62% of the office with the *High Resistance* policy or 8% of the office with the *Low Resistance* policy. Additionally, our results regarding optimized layouts for occupant reintroduction can yield significant increases (38%) to behavioral diversity patterns, a proxy for the ability to socially distance within a space, with a minimal impact on energy use (increase of 1%). This points to the potential of intelligent data-driven policies that can *both* enhance occupant safety in office spaces via socially distancing opportunities and operate in an energy-efficient manner.

Our results exhibit an overlap between the *High Social* and *Low Resistance* policies in our case study, as well as between the *Low*

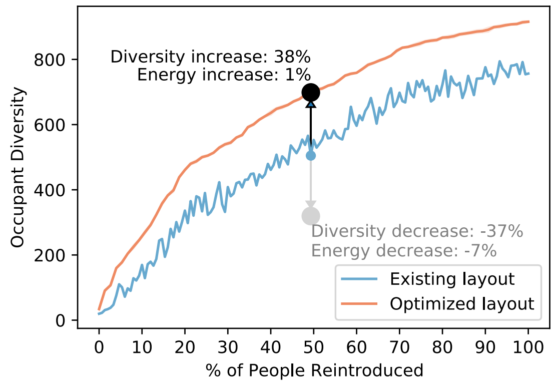

Figure 2: Occupant behavioral diversity and building energy consumption analysis for *High Social* policy.

Social and *High Resistance* policies. This near equivalency matches intuition both generally and specifically for our network, as one of the more popular immunization policies called *Targeted Immunization* also prioritizes high degree nodes and generally converges on an effective solution for immunization.

We note that this short paper represents a first step to understanding how we can introduce intelligent data-driven policies for occupant reintroduction amidst pandemic conditions. Future work is necessary to expand this work for differing conditions and leverage additional network topology features for an occupant network. For example, this analysis did not consider the role of the office's spatial network in SO network tie formation, which may result in an under-appreciation of the dependency between relationship development and physical distance. We also acknowledge that our SO network might mutate at different occupancy levels through the reintroduction process, and future work is required to estimate better the mutation patterns that might emerge. Nevertheless, our initial work highlights the role that data-driven modeling of the occupant space and SO network can have in mitigating the spread of a disease like COVID-19 and safely return workers to office spaces even in a limited capacity scenario.

In the end, our results in this short paper demonstrate the ability to leverage intelligent sensing systems and network topology based policies to define SO networks and ultimately analyze office population policies in the context of epidemic and social lenses. The tools we propose aim to aid decision making for building and organizational managers that balance safety, productivity, and sustainability objectives of their office spaces.

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