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An intelligent hot-desking model harnessing the power of occupancy sensing

ABSTRACT

In this paper we develop a model to harness the power of occupancy sensing in a commercial hot-desking environment utilising experimental data from an office in central London. Hot-desking is a method of office resource management that emerged in the 90s as a practice to reduce the real estate costs of professional practices, by abandoning traditional territorial working (i.e. where specific desks were allocated to specific employees). This was particularly desirable in high real estate cost areas such as New York, London or in high-staff, low-wage offices, or where underutilization of desk space due to remote/client site working was proved to be a significant overhead. However, the shortcoming is often in the suitability and appropriateness of allocated work environments. The Internet of Things could produce new data sets in the office at a resolution, speed and validity of which that they could be factored into desk-allocation, distributing seats based on appropriate noise levels, stay length, equipment requirements, previous presence, and proximity to others working on the same project, among many others.

In this paper we show that sensor data can be used to facilitate office resources management, in our case desk allocation in a hot-desking environment utilising activity based working (or allocating by ‘work theme’), with results that outweigh the costs of occupancy detection. Not only are we able to optimise desk utilisation based on quality occupancy data, but also demonstrate how overall productivity increases, as individuals are allocated desks of their preference as much as possible among other enabling optimisations that can be applied. Moreover, we explore how an increase in occupancy data collection in the private sector could have key advantages for the business as an organization and the city as a whole.

Categories and Subject Descriptors

H.4.1 [Information Systems Applications]: Office Automation – *Workflow management*; H.1.1.1 [Information Systems]: Systems and Information Theory – *Value of information*.

General Terms

Sensor networks, Data analytics.

Keywords: Occupancy sensing, desk allocation.

1. Introduction

1.1 Context

We currently live in a world is often described as becoming ‘increasingly digital’. That is to say, our ability to capture, process and harness value from data is becoming increasingly feasible and increasingly important.

Three key enablers to this end are regularly discussed in literature:

- **The Internet of Things (IoT)**– the concept of increasing prevalence of items with connectivity functionality (in that they can collect and transmit data, and receive and be actuated by data), both traditional IT devices such as phones and computers, but also inanimate and narrow-purpose objects, such as air conditioners, fridges, chairs and windows (Townsend, 2013).
- **Big Data (BD)** – the complementary notion that the increased quantity of connected devices is creating an exponentially growing quantity of data. This, alongside the improved abilities to store and process data presents the opportunity to garner greater insight from the world around us (Ricci, 2014).
- **Changes in culture, behaviours and value systems** – The rise of generations exposed exclusively to an internet-enabled world has shown to create distinctly different citizen expectations. Particular distinctions have been observed in expectations of service delivery times, methods of socializing and employment preferences (Armour, 2005).

Today we are also highly mindful of environmental issues, particularly global warming and fossil fuel use, and a considerable quantity of this discourse focuses on urban areas, and as such, the built environment. 54% of the world’s population live in cities, 75% of global energy use takes place inside them and 80% of our CO2 emissions are from them. By 2050, estimates are placed at urban population reaching 70%, so it is unlikely this focus is going to drift any time soon (“IBM - A Smarter Planet - Smarter Cities - Ideas - New Zealand,” 2014).

In addition, economically, businesses are constantly searching for any and all methods to decrease costs, both operational and capital, and increase revenue, both in terms of gross sales figures and profit margins. The global

financial crisis of 2007-2008 and the ensuing austerity movements have been a particular driver for reducing costs, particularly in situations where little capital investment is required and payback times are short.

These enabling technological trends, in the context of the built environment, combine to produce data-harnessing concepts, often labelled ‘Smart’. In addition, both the strong economic and environmental drivers mean that research, interest and investment into these has been strong over the last 5 years.

1.2 Smart Buildings

Within the built environment, we have seen this ‘digital’ trend having most influence in the field of Smart Cities. Today, the notion of Smart Cities is popular, profitable and academically thriving. The underlying notion that a proliferation of connectable infrastructure, distributed, personal sensors and big data could create efficient, enjoyable and sustainable cities has become one of the defining gambits of the current age (Glaeser, 2011; Townsend, 2013; Webb et al., 2011).

Curiously, using the same notion of utilizing data and connectivity within buildings however (aka, Smart Buildings), despite sharing the similarity of being scenarios of the built environment (indeed, one being essentially a significant component part of the other) has had an order-of-magnitude-smaller interest (Cole et al., 2012).

At the Barcelona Smart Cities Expo, a Cisco representative suggested that buildings had ‘locked the doors’ to the wide spread interest and awareness of intelligent, integrated data-based solutions that were sweeping the cities of the world outside, missing out on a significant amount of potential value (“Barcelona Smart Cities Expo World Congress 2014,” 2014).

Of the work that does exist in the field of Smart Buildings, research tends to be most prevenient on concepts that align with traditional engineering silos and have relatively simple value chains; ‘smart energy’, ‘smart structures’, ‘smart lighting’ and so on.

A short-coming of this is that the existing mantra – of what there is - neglects relatively new datasets that do not have an association with a traditional engineering field. The significance of this is that it neglects the consideration of data sets that do not align with a typical engineering silo, such as those surrounding the movement of people - occupancy data is the embodiment of this.

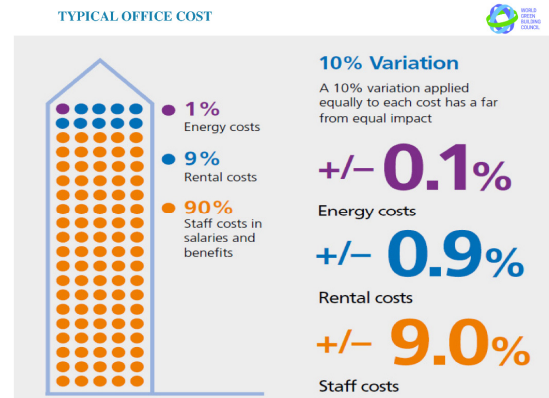


Figure 1 Analysis by the World Green Buildings Council of the average proportion of office costs associated with energy, rental and staff costs (“WorldGBC 3 :: Health, Wellbeing and Productivity,” n.d.).

This omission becomes significant when we holistically consider the financial impact of human-orientated office costs vs. utility or rental costs as displayed in Figure 1 .

1.3 Occupancy

In this paper we define occupancy as the combination of: (a.) the detection of presence, (b.) associated with a special context (e.g. space or activity) and (c.) associated with a time context, combined to create occupancy data. There is of course variation in the nature of occupancy nature depending on exactly how these three criteria are fulfilled.

Variations in the nature of (b.) and (c.) are typically one dimensional and generally result in changes in data resolution. The first point however has considerable room for multi-dimensional variation. This is far more significant, and affects what we will describe as the ‘richness’ of the data, demonstrated with examples in Figure 2.

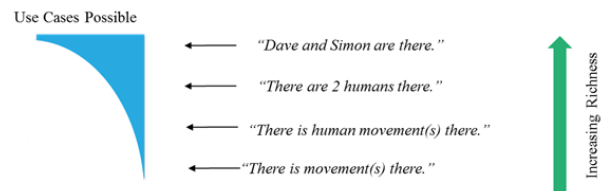


Figure 2 Variation in richness of occupancy data

While variation of space and time may indeed affect the performance of a use case, variation in actual presence determines, in a very binary manner, what use cases are and what use cases are not possible.

1.4 Hot-Desking

After the rise of the service sector in developed western economies, offices became home to an increasingly diverse range of consultancies and financial services, typified by larger office sizes and for many companies, a disassociation of hours spent working and the cost of services billed to the client. In conjunction with this, rising rental costs in the large cities where these offices needed to be located (Jones and Orr, 2004) compounded the issue of expensive real estate.

As such, minimising the cost of large office areas became increasingly important; A popular idea emerged in the late 90s to replace territorial working systems - whereby each individual is directly associated with a specific desk - with an allocation system whereby those who attend the office on a specific day are given a free desk from a pool. The key value driver of this was that office sizes could be reduced up to 30% (Harris, 1992) depending on the tendency of the business to visit clients and collaborators outside the premises. A rise in part time working (Stuart, 2014) further improved the benefit of non-territorial desk systems.

Today, the most common form of hot-desking is simply 'employee-led': on attendance to the office, an employee chooses a desk themselves that they deem to be unoccupied, and claims it for the day.

While the value case presented by hot-desking is relatively clear and by no means insignificant, such schemes have had mixed success (Höpfl and Hirst, 2011). Today's literature's criticisms can be broadly categorised into several key aspects:

- **Ineffective management** – A mixture of slow and inconsistent methods of distributing desks, ranging from 'this desk is free' signs, to entirely free-for-all situations introducing misunderstandings about whether or not a desk is occupied (Halford, 2004).
- **Loss of working synergies** – In traditional territorial (i.e. Assigned) working systems, members of a specific team are assigned desks in close proximity to one another to enable easy and regular collaboration and discussion between individuals working on similar projects and similar themes. When desks are assigned either randomly, or linearly in a 'pegs into a slot' system, this is lost. While it is difficult to attribute the impact of this on issues such as productivity and employee happiness, as we will discuss, it could be envisaged that even small variations (1% decrease in productivity) have significant impact on even the smallest scales (Millward et al., 2007).

- **Cultural and behavioural barriers** - A territorial working system encourages individuals to build and adapt their desk to their own personal preferences and working ideals; with a hot-desking system, these are lost. This ranges from sentimental issues, such as photos of loved ones and favourite literature, to working documentation, such as large drawings and annotated reports, to office furniture, such as specific ergonomic desk heights and chair configurations (Felstead et al., n.d.).

1.5 Intelligent Hot-Desking

The rise of 'Smart' enablers as detailed in the introduction provides a unique opportunity to fundamentally alter the nature of hot-desking by utilising increased data about the workplace, its occupants and their intentions and preferences. There is a considerable literature base that highlights that an employee's position, both in an absolute sense and in relation to other employees, has a strong impact on their behavior and happiness in the workplace (Westerman and Yamamura, 2007).

In principle, rather than a 'pegs into a slot' approach discussed above, intelligent hot-desking would evaluate the best position for an employee to work based on an algorithm combining a number of weighted inputs. These inputs could include, but are not limited to:

- **Noise level** (Leather et al., 2003) of working environments, derived from acoustic sensors distributed about the office. Some specific, attention-to-detail work will require quiet environments and typically generate little noise in turn. Team-focused work may not necessarily need a loud environment, but will be able to function in one, and will certainly contribute to the noise. In an anonymised interview, one large bank client of an international engineering consultancy stated that one of the top 3 factors preventing their company from being more profitable was an inability to effectively manage noise-sensitive and noise-making work/ groups in the office (Anonymized Director at Major UK Banking Firm, 2012).
- **Duration of stay** derived from calendar data, or asked for at on-arrival desk requests. Individuals staying for exceptionally short periods of time may simply require a smaller 'touch down desk'. This may further improve the floor area savings of traditional hot-desking.
- **Nature of work** (Sydow et al., 2004), potentially derived from a 'work theme hashtag' system, where keywords for the type and project of work

could be requested from individuals for a given day or calendar period. This element will enable individuals to recapture the benefit of working alongside those who are of an ilk to them, as associated with traditional working systems. Indeed, this ‘proximity synergy’ may be better than traditional allocated systems for two reasons. Firstly, desk associations are typically totally reevaluated on anything from a yearly to 10-yearly basis – people may switch specific teams within these times but the territorial system is slow to update for this. Secondly, this system opens up new dimensions on which people may want to collaborate. Traditionally, being in the same engineering discipline, for example, may have been the fundamental decider of desk position. However, now, people can align by working on a specific project. In general, this is only currently done on extremely large ‘megaprojects’, such as the London 2020 Olympics (“IBM - A Smarter Planet - Smarter Cities - Ideas - New Zealand,” 2014), but evidence suggests these create powerful working environments, and there is a suggestion that, if it could be made practical, similar benefits would be realised for such groupings for smaller projects. Last but not least, it also caters for individuals who are ‘multi-speciality’, and are now enabled to sit with the appropriate group when working on a particular topic.

- **Environmental preferences** (Westerman and Yamamura, 2007) derived from many types of dataset, including temperature and light sensors across the office. Many small but psychologically significant issues could be improved by consideration of individual’s preferences. For example, individuals who prefer a warmer office environment could be placed further away from colder areas, typically atriums and stairwells. Alternatively, those more susceptible to influences from daylight on their mood could be placed closer to the window.
- **Desk configuration**, derived from asset location and management information. A relatively simple, but logistically significant benefit is enabling individuals to select the exact kind of office equipment they need that day, such as multiple monitors or a particularly powerful desktop computer unit.
- **Otherwise held personal preferences**, derived from occupant feedback. It could be possible that a system that evaluated how you felt about your selection of desk for the day can gradually deduce preferences to specific seats that cannot be

explained by the above characteristics or even an individual’s intuition.

Of course what combination of these is most appropriate to a given office will be heavily context-dependent

1.6 Purpose

It is clear that there are significant shortcomings to the use of hot-desking within a commercial office environment, which can be broadly translated to influences on employee productivity. These are inherently hard to quantify.

It is equally clear however that in this ‘digital age’, we now have the ability to accurately understand the state and characteristics of the workplace and its element, and take action on this data – namely begin to distribute desks with intelligence.

While it is apparent from the outset that this is possible, little research exists on how optimization might look in practice, nor the value it could bring to the workplace.

Within this paper we will explore the potential for Intelligent Hot-desking to bring about superior working conditions (in the form of increased productivity) in comparison to a Traditional Hot-desking Systems.

To demonstrate this we will use a distribution based on one data type for simplicity. We will select the distribution logic of ‘work theme’ within a demonstrator context of an engineering consultancy’s commercial office, facilitated by primary data. ‘Work theme’ has been selected for the following reasoning:

- It is relatively easy to collect primary data on employees typical work type patterns, over more detailed aspects such as noise generation.
- It works around a hypothesis of creating ‘positive’ working benefit, rather than avoiding ‘negative’ working obstacles
- In theory all employees of the office are involved, on the logic all have work of a certain type.

As such our objectives are as follows:

1. Establish a modelling framework, context and distribution algorithm for our scenario.
2. Observe the practical workings of an Intelligent Hot-desking System throughout a simulated day.
3. Deduce an estimate for the improvement in productivity that Intelligent Hot-desking Systems could bring over Traditional Hot-desking Systems.
4. Discuss the potential barriers and enablers to implementation of Intelligent Hot-desking Systems.

2. Modelling

2.1 Philosophy

We will principally address the situation as a discrete events simulator focusing on the office as a series of slots, relating to desks; each of which either have individuals in or do not. Each individual will have characteristics, some of which are input (relating to their intentions) and some of which are output (relating to how their working environment has influenced them).

On arrival, an algorithm will decide the place for an individual to sit for a given timespan for a given desk allocation system and distribution type.

While an individual is in a desk, for every unit time that progresses, the quality of the environment will be assessed. The simulation will run for 1 day, with 1 minute clock pulses. The values for each person-time-quality will be summed each second, for the day, giving a selection of overall 'scores' for a given allocation system.

This process will be run for an 'intelligent' hot desk distribution, and a 'traditional' distribution desk distribution, detailed below.

2.2 Individuals

2.2.1 General

For the behaviour of individuals we will be using primary observational data collected from an anonymised office of an engineering consultancy. The observed scenario has the following characteristics:

Office grid: 12x12 individuals

Total attendees: 155

2.2.2 Arriving time and Leaving time

In practice, the time spent in the office will vary distinctly between individuals. Support staff, such as HR and Accounting are unlikely to ever leave for off-site work. Low and middle-ranking general employees are likely to attend client sites on occasion, and high-ranking staff, whose role include client relation management and thought-leadership, are likely to regularly leave, and be, out of office. These are of course generalisations and the exact spread and nature of office attendance will depend on organisational size, office size, industry and organisational culture.

By observation of swipe gate data from our office, we can see that flow to the office in our scenario is a combination of:

- A) Traditional morning and evening peaks for entrance and exiting to the office.
- B) Between these, a lesser, broader flow of assorted leaving and re-entering of the office for various

business engagements. The leaving is centred around before lunch, the arriving centred after lunch.

The first is relatively easy to simplify for repeatability in the model; the latter will require considerable simplification. Fitting normal distributions, we will estimate the probability of an individual entering the office over the course of the day and the probability of an individual who is in the office, leaving an office, as the sum of the following weighted distributions:

- *Arriving: $w1*A+w2*B$; $w1=1-w2$*
 - *A: Norm (8.5,1), $w1=0.7$*
 - *B: Norm (13,5), $w2=0.3$*
- *Leaving: $y1*A+y2*B$; $y1=1-y2$*
 - *A: Norm (18,1), $w1=0.7$*
 - *B: Norm (13,5), $w2=0.3$*

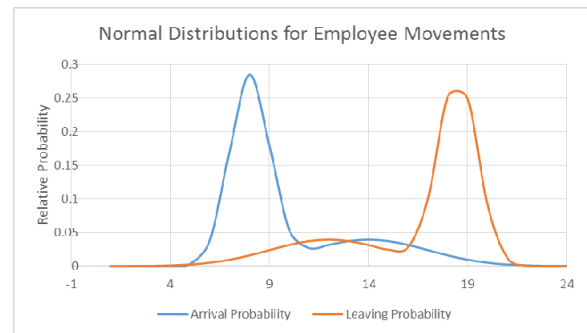


Figure 3 Arrival and Leaving probability distributions

Figure 3 displays this graphically. These estimates will serve as a reasonable assumption for a generic context – variation will exist between different companies and different industries.

We will also simplify as to there being no inter-relation between comings and goings of individuals - if an individual arrives late to the office, they are just as likely to leave for a meeting as they are as someone who has been there since early. We will deem this an acceptable simplification. Furthermore, employees will only be able to enter and leave the premises once. The probability distributions will in effect simulate real return visits as new individuals.

Lunch and other temporary breaks have been ignored as observation demonstrates that desks remain allocated during these periods.

2.2.3 Workgroup Distributions

In the wider group of staff from which our sample is taken, work types are quantified by several large groups and several relatively niche groups. The distributions of work type in our primary data are: *Type A: 0.4, Type B: 0.3, Type C: 0.15, Type D: 0.1, Type E: 0.05*

Indeed, while this specific distribution may not be the reality in all samples, our research suggests this is not unusual for the industry from which the examined organisation is from.

2.3 Productivity

For productivity it would be ideal to create a quantitative value for the increase in productivity, and this may be a feasible end goal for later research, but for purposes of this modelling, we will settle with relative metrics for comparing different experiences, rather than a unit that is immediately bounded to any physical or financial reference.

As such, we will explore how much more time people spend around those who are working on the same work type as they are, compared to ‘less intelligent’ distributions.

There is no documented method for assessing the level or quality of interaction between two individuals in the workplace and the distance between their desks; as discussed, research has simply shown that the quality, with respect to pragmatic business ends, appears to be higher when ‘the right’ individuals are in a ‘close proximity’.

For purposes of a broad estimation, drawing on existing literature, the ability to speak to one another is regularly cited as a beneficial consequence of sitting near another individual (Cole et al., 2012) and so we will use the behaviour of noise to model these relationships, in particular the square law. A series of unstructured interviews with staff in this workplace validated this relationship at a conceptual level.

As such, we depict individuals as being able to project an ‘area of interaction’ of positive working influence in their proximity with square-law decay. Other individuals will be positively affected by the level of *relevant* (of the same work type) area of interaction projected on their desk by any number of surrounding staff. These will sum linearly when several relevant areas of interaction all fall upon a person’s desk. We will model *irrelevant* aura as having neither positive nor negative effect.

We will assume desk units have a size of 2.5m boundary from observation in our scenario, and that noise values are measured 0.5m from the centre of the unit – again, a realistic point of someone’s seat from observation of scenario. We will then use basic square law as an estimate:

$$I_2 = \left(\frac{d_1}{d_2}\right)^2 * I_1$$

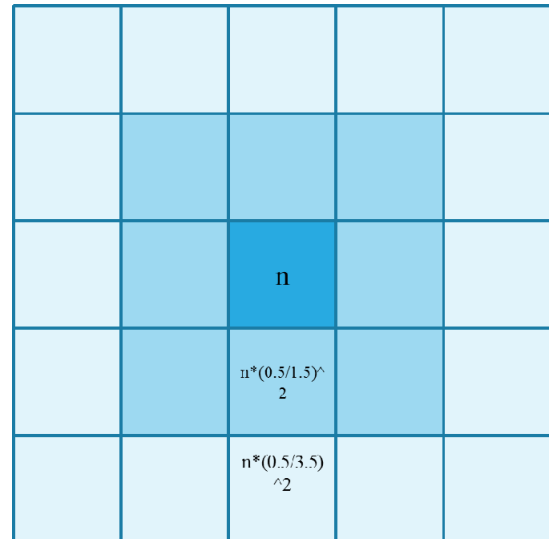
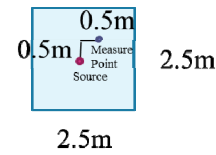


Figure 4 Propagation of positive work theme environment

For simplicity, we will ignore diagonal inaccuracies.

As seen in Figure 4, n will start at 25, to produce a value of 1 for individuals in the closest possible proximity – the immediate row. This then produces positive values of:

1st Row: 1

2nd Row: 0.25

3rd Row Onwards: (neglected for simplicity)

As can be observed, if an individual is surrounded in the first row on all sides by staff on the same work, a value of 8 (8x1) can be achieved. If the second row is also fully occupied with relevant staff, a value of 12 can be achieved (8x1+16x0.25), the maximum achievable. Furthermore, there is of course a synergy – when there are two individuals, they are both improving each other’s working environment, so the total ‘quality of environment’ goes from 0 (with one person) to 2 (with both).

In reality the relationship is likely to be more discrete than modelled – it is more probable that there is a threshold where an individual will either opt to interact or not, rather than ‘half interact’; as such, these values can be considered as probabilities that a positive work interaction will take place, and will serve as broad estimations.

2.4 Intelligent Hot-Desking Distribution Process

There are several methods by which we could evaluate the distribution of the desks in this system. These include:

1. **On-arrival, current-state individual-optimisation** – In a system where no pre-advice is given as to who will be in and who shall not, the seat is allocated to maximise the conditions for the arriving individual based on information for the exact moment they enter, hoping conditions stay favourable and ignoring impact on those already present.
2. **On-arrival, current-state group-optimisation** – In a system where no pre-advice is given as to who will be in and who shall not, the seat is allocated to maximise the net conditions for all currently in the office, based on information for the exact moment they enter, hoping conditions stay favourable.
3. **Full-term, group-optimisation** – In a system where pre-advice is given as to who will and will not be in (including duration of stay), the seat is allocated to maximise the net conditions for all individuals intending to arrive that day, considering all permutations of seating.

It is clear that the more advanced the system, the more ideal the seating locations and the higher the net gain overall.

For purposes of computational simplicity, and to avoid reviewing a distribution process with significant cultural barriers to implementation, we will use Method 2 in this instance.

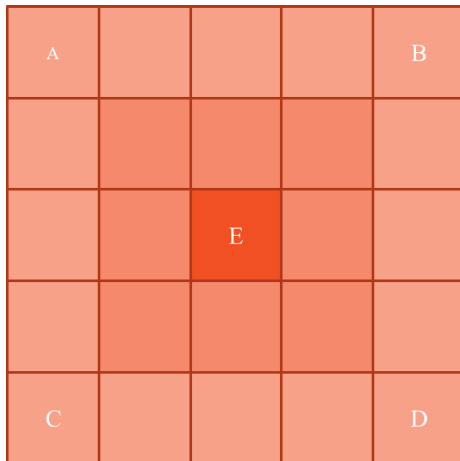


Figure 5 Tie-breaker distribution logic

By observation it can be considered that systems 1 and 2 will struggle with early arrivals to the office as many permutations are identical – yet their decision will strongly influence the rest of the day. As such a tie-breaker logic is required.

After experimentation of several tie-breaker systems, the most effective was settled upon. When there is no difference in the distribution nature, the system will attempt to send a given work type as close to a predefined extremity of the office it has preassigned to that work type; these will be each of the 4 corners, plus the centre of the grid. In effect, the distribution has a disposition to form colonies when no better distribution logic is available. This is displayed graphically in Figure 5.

Hot-Desking Distribution Process

For the hot-desking process we will review three similar variations:

1. That individuals come in and are allocated a desk at random from free desks, with no logic applied.
2. That individuals come in and are given a desk in a ‘closest desk free’ (to the top left of the office) system. Essentially, this is the linear, ‘pegs into a slot’ distribution that has already been discussed.
3. For means of understanding its influence, we will simulate a distribution that simply has the ‘extremities’ tie-breaker logic only, and aims to throw individuals as close to the predefined extremities, and does none of the evaluation in the intelligent system.

3. Results

3.1 Modelling

Firstly we will observe the office at time ‘slices’ throughout the day, when desks have been allocated as per the intelligent system. This will be expressed through two diagrams:

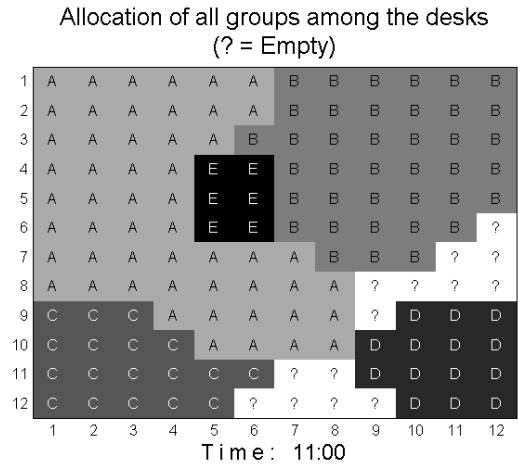
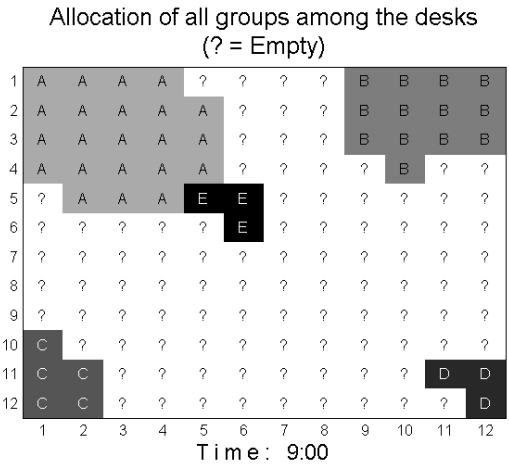


Figure 6 Snapshot of all groups' allocation among desks

The first diagram, seen in Figure 6 entails a graphical representation of the position of different work themed individuals, labelled by their work theme, or an empty office space, designated by "?". Note this is demonstrational and not part of a modelled test.

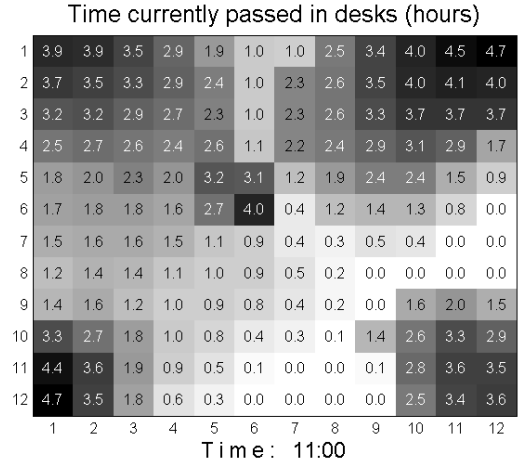
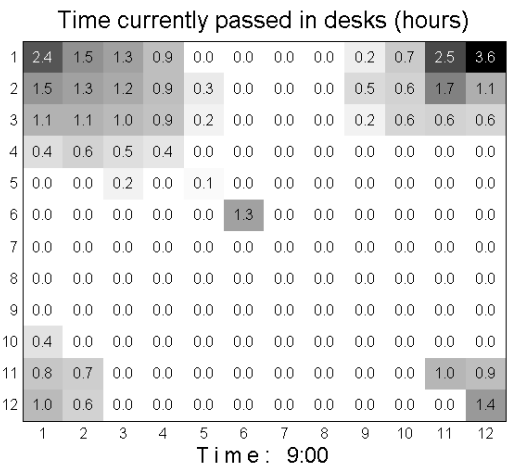
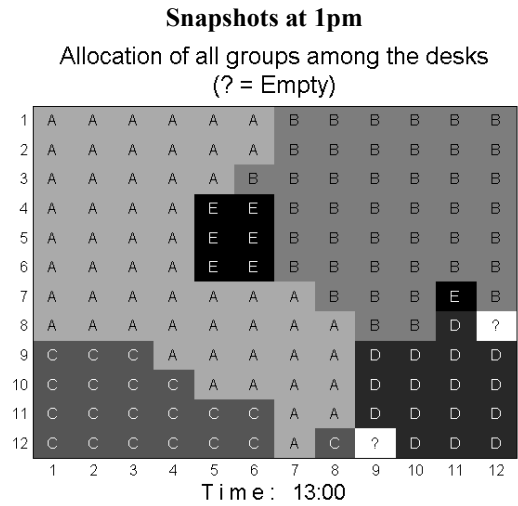


Figure 7 Time spent by employees in their desks

Figure 7 demonstrates the duration an individual has been at the desk. Note that all times are rounded to 1 d.p., so zero does not necessarily specify an empty desk.

We will now examine slices of the scenario.

Snapshots at 11am



Time currently passed in desks (hours)

1	5.9	5.9	5.5	4.9	3.9	3.0	3.0	4.5	5.4	6.0	6.5	6.7
2	5.7	5.5	5.3	4.9	4.4	3.0	4.3	4.6	5.5	6.0	6.1	6.0
3	5.2	5.2	4.9	4.7	4.3	3.0	4.3	4.6	5.3	5.7	5.7	5.7
4	4.5	4.7	4.6	4.4	4.6	3.1	4.2	4.4	4.9	5.1	4.9	3.7
5	3.8	4.0	4.3	4.0	5.2	5.1	3.2	3.9	4.4	4.4	3.5	2.9
6	3.7	3.8	3.8	3.6	4.7	6.0	2.4	3.2	3.4	3.3	2.8	1.9
7	3.5	3.6	3.6	3.5	3.1	2.9	2.4	2.3	2.5	2.4	1.7	0.8
8	3.2	3.4	3.4	3.1	3.0	2.9	2.5	2.2	1.5	1.2	0.8	0.0
9	3.4	3.6	3.2	3.0	2.9	2.8	2.4	2.2	1.7	3.6	4.0	3.5
10	5.3	4.7	3.8	3.0	2.8	2.4	2.3	2.1	3.4	4.6	5.3	4.9
11	6.4	5.6	3.9	2.9	2.5	2.1	1.6	1.5	2.1	4.8	5.6	5.5
12	6.7	5.5	3.8	2.6	2.3	1.2	1.3	1.2	0.0	4.5	5.4	5.6
	1	2	3	4	5	6	7	8	9	10	11	12

Time : 13:00

Snapshots at 2pm

Allocation of all groups among the desks
(? = Empty)

1	A	A	A	A	A	A	B	B	B	B	B	B
2	A	A	A	A	A	A	B	B	B	B	B	B
3	A	A	A	A	A	B	B	B	B	B	B	B
4	A	A	A	A	E	E	B	B	B	B	B	B
5	A	A	A	A	E	E	B	B	B	B	B	B
6	A	A	A	A	E	E	B	B	B	B	B	B
7	A	A	A	A	A	A	B	B	B	E	B	B
8	A	A	A	A	A	A	A	B	B	D	?	?
9	C	C	C	A	A	A	A	A	D	D	D	D
10	C	C	C	C	A	A	A	A	D	D	D	D
11	C	C	C	C	C	C	A	A	D	D	D	D
12	C	C	C	?	C	C	A	C	D	D	D	D
	1	2	3	4	5	6	7	8	9	10	11	12

Time : 14:00

Time currently passed in desks (hours)

1	6.9	6.9	6.5	5.9	4.9	4.0	4.0	5.5	6.4	7.0	7.5	7.7
2	6.7	6.5	6.3	5.9	5.4	4.0	5.3	5.6	6.5	7.0	7.1	7.0
3	6.2	6.2	5.9	5.7	5.3	4.0	5.3	5.6	6.3	6.7	6.7	6.7
4	5.5	5.7	5.6	5.4	5.6	4.1	5.2	5.4	5.9	6.1	5.9	4.7
5	4.8	5.0	5.3	5.0	6.2	6.1	4.2	4.9	5.4	5.4	4.5	3.9
6	4.7	4.8	4.8	4.6	5.7	7.0	3.4	4.2	4.4	4.3	3.8	2.9
7	4.5	4.6	4.6	4.5	4.1	3.9	3.4	3.3	3.5	3.4	2.7	1.8
8	4.2	4.4	4.4	4.1	4.0	3.9	3.5	3.2	2.5	2.2	1.8	0.0
9	4.4	4.6	4.2	4.0	3.9	3.8	3.4	3.2	2.7	4.6	5.0	4.5
10	6.3	5.7	4.8	4.0	3.8	3.4	3.3	3.1	4.4	5.6	6.3	5.9
11	7.4	6.6	4.9	3.9	3.5	3.1	2.6	2.5	3.1	5.8	6.6	6.5
12	7.7	6.5	4.8	0.0	3.3	2.2	2.3	2.2	0.2	5.5	6.4	6.6
	1	2	3	4	5	6	7	8	9	10	11	12

Time : 14:00

Snapshots at 3pm

Allocation of all groups among the desks
(? = Empty)

1	A	A	A	A	A	A	B	B	B	B	B	B
2	A	?	A	?	A	A	B	B	B	B	B	B
3	A	A	A	A	A	B	B	B	B	B	B	B
4	A	A	A	A	?	E	B	B	B	B	B	B
5	A	A	A	?	E	E	B	B	?	?	B	?
6	A	A	A	A	E	E	B	B	B	B	B	B
7	A	A	A	A	A	A	A	B	B	B	E	B
8	A	A	A	A	A	A	A	A	B	B	D	?
9	C	C	C	A	A	A	A	A	D	D	D	D
10	C	C	C	C	A	A	A	A	D	D	D	D
11	C	C	C	C	C	C	A	A	D	D	D	D
12	C	C	C	?	C	C	A	C	D	D	D	D
	1	2	3	4	5	6	7	8	9	10	11	12

Time : 15:00

Time currently passed in desks (hours)

1	7.9	7.9	7.5	6.9	5.9	5.0	5.0	6.5	7.4	8.0	8.5	8.7
2	7.7	0.0	7.3	0.0	6.4	5.0	6.3	6.6	7.5	8.0	8.1	8.0
3	7.2	7.2	6.9	6.7	6.3	5.0	6.3	6.6	7.3	7.7	7.7	7.7
4	6.5	6.7	6.6	6.4	0.0	5.1	6.2	6.4	6.9	7.1	6.9	5.7
5	5.8	6.0	6.3	0.0	7.2	7.1	5.2	5.9	0.0	0.0	5.5	0.0
6	5.7	5.8	5.8	5.6	6.7	8.0	4.4	5.2	5.4	5.3	4.8	3.9
7	5.5	5.6	5.6	5.5	5.1	4.9	4.4	4.3	4.5	4.4	3.7	2.8
8	5.2	5.4	5.4	5.1	5.0	4.9	4.5	4.2	3.5	3.2	2.8	0.0
9	5.4	5.6	5.2	5.0	4.9	4.8	4.4	4.2	3.7	5.6	6.0	5.5
10	7.3	6.7	5.8	5.0	4.8	4.4	4.3	4.1	5.4	6.6	7.3	6.9
11	8.4	7.6	5.9	4.9	4.5	4.1	3.6	3.5	4.1	6.8	7.6	7.5
12	8.7	7.5	5.8	0.0	4.3	3.2	3.3	3.2	1.2	6.5	7.4	7.6
	1	2	3	4	5	6	7	8	9	10	11	12

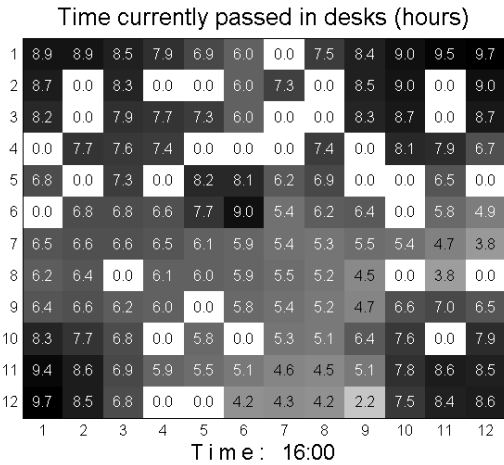
Time : 15:00

Snapshots at 4pm

Allocation of all groups among the desks
(? = Empty)

1	A	A	A	A	A	A	?	B	B	B	B	B
2	A	?	A	?	?	A	B	?	B	B	?	B
3	A	?	A	A	A	B	?	?	B	B	?	B
4	?	A	A	A	?	?	?	B	?	B	B	B
5	A	?	A	?	E	E	B	B	?	?	B	?
6	?	A	A	A	E	E	B	B	B	?	B	B
7	A	A	A	A	A	A	A	B	B	B	E	B
8	A	A	?	A	A	A	A	A	B	?	D	?
9	C	C	C	A	?	A	A	A	D	D	D	D
10	C	C	C	?	A	?	A	A	D	D	?	D
11	C	C	C	C	C	C	A	A	D	D	D	D
12	C	C	C	?	?	C	A	C	D	D	D	D
	1	2	3	4	5	6	7	8	9	10	11	12

Time : 16:00



Day Overview

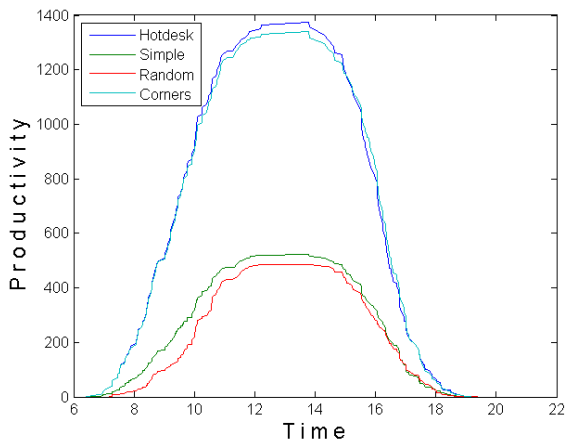


Figure 8 Total Productivity (purely in terms of workplace quality, as discussed above) per distribution method

The summed productivities of all individuals in the office by each distribution method can be seen, per hour, in Figure 8.

3.2 Observations

We can observe in our experimental scenario, the influence of the tie-breaker logic is extreme. By 11am when the majority of the am peak has entered, the office is at a high occupancy.

By 2pm, as some individuals leave and others attend, we can begin to observe the algorithm making decisions between several sub-optimal configurations and improving over the extremities system. Our scenario however does not have sufficient coming and going for this aspect of the algorithm to bring about a significant benefit over the extremities-only optimization. The extremity-optimization is still the dominant feature of the organization. By 4pm,

the office is sufficiently clearing out from the beginning of the pm peak that when new entrants arrive, there is a high probability of a reasonable desk choice being a distributed extremity, so again, the intelligent algorithm loses advantage. An increase in the number of work groups, which is a very possible real world situation, would also favor the more intelligent distribution.

Compared to a standard hot-desking situation however, from our results it appears that over the core hours of the day, our system of allocation has produced approximately 2.8 times the improvement of seating location – using our relatively metric - over the two traditional methods of desk allocation.

4. Conclusion

4.1 Overview

We have demonstrated that within the context of our scenario, the use of intelligent desk distribution can significantly improve the proximity an employee to others working on the same theme of work. This in turn is believed to improve the productivity of these employees based on existing research and literature.

As has emerged from the results, it has been observed that the initial ‘tie-breaker’ logic of creating ‘colonies’ of work themes in the extremities of offices is, at least in our scenario, bringing about the vast majority of this productivity improvement. This of course is still a form of intelligence, and a certain degree of occupancy sensing (to understand the current allocation of desks) is essential to this end.

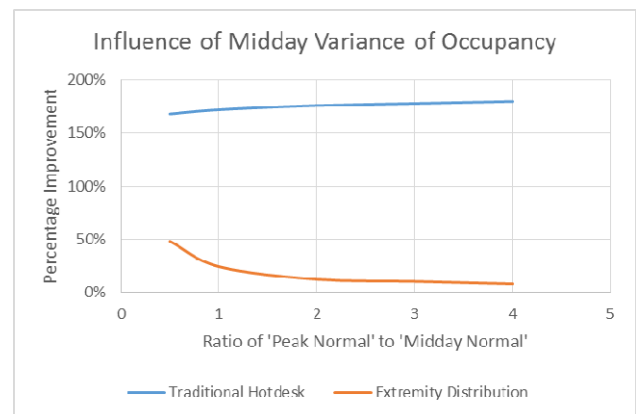


Figure 9 Sensitivity Analysis to degree of coming and going

Observation suggests that the level of significance of the main part of our allocation logic is heavily dependent on the level of coming and going within the office and the ‘tightness’ of the office space (i.e. How close to maximum capacity it is run). Running a simple sensitivity analysis and varying performance improvement of the intelligent

system vs traditional hot desk and ‘extremity only’ distribution in Figure 9 demonstrates that this maintains the case until midday flow becomes more powerful than AM/PM peaks, something that is unlikely to be observed in practice. Part of the reason for this is that the average occupancy then becomes lower, so the likelihood of an extremity decision being reasonable increases. The improvement of the intelligent system over the extremity system would be higher than shown in Figure 8 if the number of staff attending the office was raised, as the midday flow was weighted more heavily.

As discussed, it is difficult to translate how this improvement of workplace seating will translate directly into productivity improvement. In theory, there are two fundamental embodiments of productivity we can consider, and each has associated caveats:

A) Improvement in quality of work produced

- Not all industries operate on a better work is a better outcome model, with many trying to complete as much work of a minimum standard as possible.
- Quality is a difficult issue to quantify, requiring a number of complex qualitative metrics to be considered.
- Realising value in this increase in quality, for example through raising the price of the work you’re undertaking, is subject to multiple commercial caveats and highly complex.

B) Improvement in quantity of work produced

- Psychologically, there is an evidence base that suggests people’s productivity has a systematic rebound when ‘mechanical’ systems improve their productivity, known colloquially as tasks ‘filling the time you give them’, suggesting business expectations would need to change to fully realise these improvements.
- An actual improvement in workflow capacity can only be monetised if additional work is then acquired to fill the spare capacity, which is dependent on complex market externalities.
- Alternate methods of monetisation, such as laying off a member of staff to maintain the same overall workflow capacity in an environment of higher individual productivity is likely to receive considerable cultural backlash.

On balance, we will use a *quantity* interpretation of productivity.

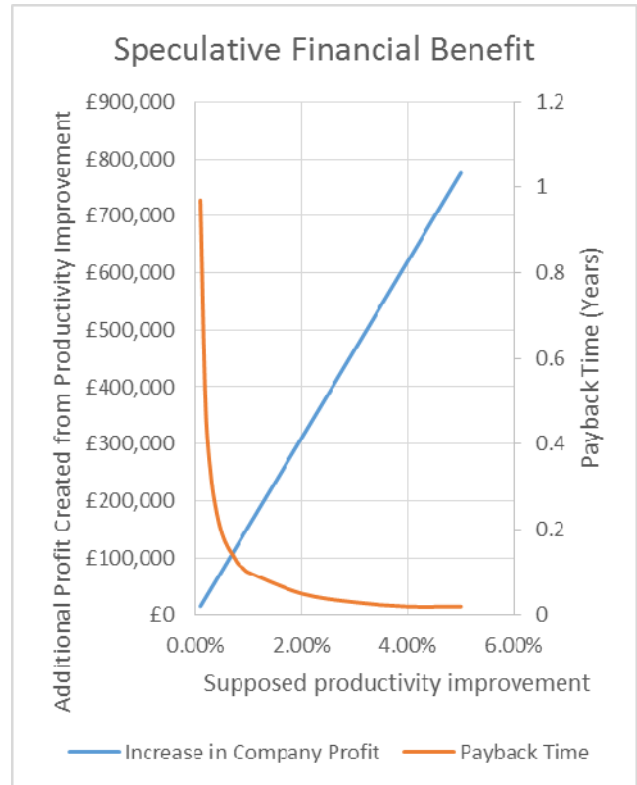


Figure 10 Annual value gain based on productivity increase

Using a 100 person office simulation (Cooper et al., 2015), Figure 10 demonstrates the varying effects, in terms of staff hours and all associated costs, of different levels of productivity improvement. In reality, this assumes a complete ‘re-billability’ of time savings; in other words, all time saved is then put back into more work, which will not always practically be the case. However, even if only a tenth of the saved time is put to effective use, a modest productivity improvement – such as 0.5% - will pay back the estimated costs of installation of such a system (estimated at £15,000 (Iraki, 2015)) would be paid back within 2 years. Compared to other analysis regarding the effects of other office conditions on productivity – such as environmental factors – which have observed ~10% improvements in productivity (“WorldGBC 3 :: Health, Wellbeing and Productivity,” n.d.) this is at least an order of magnitude smaller and as such viable in theory.

Productivity Improvement / Cost of System	£	5,000	£	10,000	£	20,000	£	50,000	£	100,000
0.1%		0.3		0.6		1.3		3.2		6.5
0.2%		0.2		0.3		0.6		1.6		3.2
0.3%		0.1		0.2		0.4		1.1		2.2
0.4%		0.1		0.2		0.3		0.8		1.6
0.5%		0.1		0.1		0.3		0.6		1.3
0.6%		0.1		0.1		0.2		0.5		1.1
0.7%		0.0		0.1		0.2		0.5		0.9
0.8%		0.0		0.1		0.2		0.4		0.8
0.9%		0.0		0.1		0.1		0.4		0.7
1.0%		0.0		0.1		0.1		0.3		0.6

Figure 11 Payback time, in years, of an implemented system within a 100 person office, at varying productivity and cost levels.

A sensitivity analysis of payback years can be seen in Figure 11.

4.2 Barriers and Enablers

It is important to realise that Methodology 2, as tested here due to simplicity, may actually be the best possible distribution method for a client, if they do not have nor wish to bring about the cultural change of specifying office attendance in advance. It is difficult to imagine a scenario where Methodology 1 would be preferred to Methodology 2 as the difference in processing complexity is minor.

Indeed, in our example, even specifying work theme in advance will require an effective system for individuals to state their work theme type. The easiest method of this may be for a running narrative of the office’s current major work themes to be maintained, then for individuals to simply choose one of these major types (or a generic ‘other’) on arrival, perhaps with the push of a button on a touchscreen. This would avoid any complicated systems of needing to pre-specify, be it in calendars or elsewhere, an individual’s work theme. Furthermore, this would enable the system to be entirely anonymous, a likely point of privacy concern for participants.

All results here also assume that individuals will be maintaining a given work theme for the entirety of their visit. Indeed, this will not be the case – in our scenario individuals engaged occasionally in work themes outside their main work theme over the course of a day. The extent to which this was the case however was not quantified specifically.

Indeed, the popularity of Intelligent Hot-desking Systems in commercial office contexts will depend heavily on the business and industry in question. Level of suitability may well mirror those typical of traditional hot-desking - where the cost of labour is high in relation to real estate costs are likely to favor maintaining a territorial working environment. However, there may be interesting niches within high-wage industries where concepts - such as 100% staffing models experiencing growing popularity in strategy consulting and product design - may favor project-based allocation.

There exists the potential to over-optimize a workspace also, and this is a concern we have not addressed. In theory, the paradigm of multidisciplinary thinking states that many highly successful, innovative ideas can come out of different disciplines interacting. As such, overly segregating employees could be damaging to objectives even harder to quantify – such as innovation – than productivity. Perhaps in the ‘smart workplace’ informal meeting areas – atrium seating, coffee spots and such – will become the home to this form of multidisciplinary interaction.

Considering the cost of implementing the sensing for such a system, it is notable that this infrastructure may be shared across a number of other Smart Building use cases.

Related to this, broadening our perspective, a significant source of value in intelligent hotdesking comes from the reusability of the occupancy data it creates. There are many possible incarnations of this.

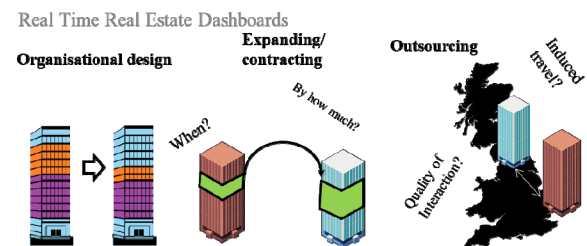


Figure 12 Potential Real Time Real Estate Dashboard use cases, where occupancy data collected through an Intelligent Hotdesking System could be used to further value.

One significant example would be the consideration of a real estate strategy, some use cases of which are embodied in Figure 12. At present, undertaking analysis of the future real estate requirements of large, multi-office commercial entities requires slow and expensive specialist studies (Cooper et al., 2015). Certain systematic considerations of these requirements cannot be accurately estimated even in these studies, such as the likelihood to induce travel when certain teams are moved to separate offices, or the varying time consumption of face-to-face meetings vs. emails (Cooper et al., 2015). Rich occupancy data – the kind that could be generated in an intelligent hotdesking system, depending on the sensing methodology – could allow these analytics rapidly and at minor cost.

Externally, this data may also have value in a ‘data ecosystem’. As big data analytics becomes a popular theme for innovative business strategies, companies are increasingly expanding their horizon on where to look for valuable data for their organization. For example, initial discussions have emerged where taxi companies are interested in purchasing anonymized building occupancy data from companies fielding ‘intelligent lifts’, so as to

rapidly detect and capture the trade associated with those leaving buildings (Cooper, 2014).

Expanding our consideration of value further, there is also a value case to this occupancy data for the city. There is increasing discussion that data collected as the private sector becomes more 'digital' is of use to the city. For example, the occupancy data of buildings could be used to adjust the frequency of nearby metro services in real time (Cooper, 2014).

Finally, and more specifically to intelligent hotdesking rather than occupancy data, this concept helps to -facilitate one of the fastest growing office segments in London – short term office hire (*Influence of Smart Buildings on the Short Term Office Market*, 2015). Through user-recognition, these systems can not only simplify the payment for per-desk-per-hour real estate models, but also ensure these highly diverse office communities are structured in a logical way.

4.3 Further Work

Within the example of work theme, it would be beneficial to understand the further benefit possible with more advanced optimization with Methodology 3 (pre-supplied duration information), the difficult implementation considerations notwithstanding.

Outside of this example, optimisations for noise and environmental conditions will have distinctly different dynamics as it will then be possible to have negative influence on others as well as positive. Following this, multi-dimension optimization could be explored.

An underlying assumption throughout this paper is that it is theoretically possible to assume all of the data necessary to action distribution. This is certainly the case in practice, but there is no consistently 'ideal' sensing methodology for this, with different sensing systems - such as PIR, pressure sensors, RFID tags – each carry their own cultural, cost and performance aspects that would need to be studied before these systems could be implemented (Cooper et al., 2015).

Ultimately, Intelligent Hot-desking appears to have the potential to bring about transformative change in the commercial office workplace backed by a strong value case. The exact value such schemes bring however, will be highly-dependent on the type and methodology of implementations, and it is the opinion of this paper that significant research, specifically simulation, needs to be undertaken on this topic. Primary research in the form of experimentation and observation, to better understand the specific productivity benefit of better workplace arrangement, would be highly influential in drawing in industrial interest.

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