Poster Abstract: On Human Behavioral Patterns in Elevator Usages

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Abstract

Elevators are the primary method for occupants to move between floors inside modern buildings. Therefore, there have been efforts in minimizing the service delay for a elevator call. Recently, the industry has started to leverage human behavioral patterns in optimizing the elevator dispatching algorithm. However, we argue that it is difficult to judge their gains in the real world, mainly due to the lack of real-world data sets and analysis based on human behavior. We take the first step in studying the human behavioral patterns in the elevator usage. Our analysis is based on real-world traces collected from 12 elevators in an 18-story office building.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Algorithms, Measurement, Experimentation

Keywords

Elevators, Energy efficiency, Comfort, Human Behavior

1 Introduction

Elevators have been one of the driving forces behind modern structures such as skyscrapers, with over 1,000,000 elevator units in North America [2]. While building efficiency has been an active research area in the past few years,the attentions have mostly been related to human comfort such as air conditioning unit and lighting. With elevator's increasing presence and impacts to buildings' and occupants' efficiency, we argue that elevator usages deserve a closer look.

The main challenge of optimizing elevator usage efficiency lies in balancing constraints from both building operators and occupants. Considering that several elevator manufacturers have estimated that elevators can contribute up to 15% of a building's energy consumption [5, 1], building owners aim to minimize the energy consumption. On the other hand, building occupants prioritize the service time of an elevator call over the other metrics. For example, it has been estimated that most people get impatient if the elevator car does not arrive within 20 seconds after they press the service call button [6].

Given humans are the sole user of elevators, we argue that understanding human behavioral patterns is an important step towards better elevator usage efficiency. In fact, this is a trend in the industry, with the push of a series of smart elevators in the past few years [3, 4]. For example, the Marriott Marquis hotel in New York City requires passengers to enter the destination floor on a panel *before* getting on the cars, and the motivation is to group passengers moving to the same floors. However, we argue that it is difficult to judge their gains in the real-world, mainly due to the lack of real-world data sets and analysis based on human behavior. Therefore, our **contributions** lie in tying the daily elevator usages to human behavioral patterns. We use a month-long data trace of 12 elevators in an 18-story office building to demonstrate the usable elevator usage patterns.

2 Elevator Usage Patterns

2.1 Data Set Descriptions

We collected the usage data of 12 elevators at an office building over a period of four weeks. The office building has 18 stories, with approximately 2,000 occupants. 12 elevators are evenly divided into two groups (one at each side of the hallway). The elevators are manufactured by ThyssenKrupp, and each unit has a serial data port that outputs real-time elevator status every second. The elevator status includes the current floor, door open/close, traveling direction, overweight alerts, etc. From the raw data, we extract the notion of "trips". We define a trip as the time between the elevator starts moving due to dispatching command, and the door closes after the last passenger gets off. For each trip, we note the floors and the timestamps when the elevator stopped.

With this dataset, we examine the elevator usage pattern in both spatial and temporal domains. Our goal is to demonstrate usable spatial and temporal patterns that can improve the elevator usage efficiency.

2.2 Spatial Analysis

Figure 1 compares the load among all the elevators with two metrics: the total number of distance (or floors) traveled, and the number of floors stopped. While the figure plots

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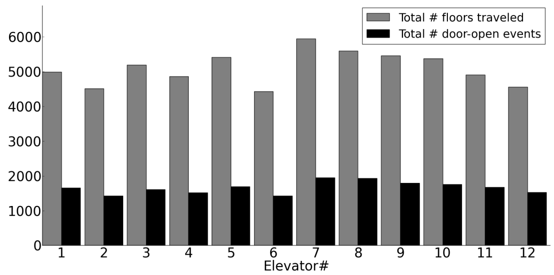

Figure 1. The load of each elevator on a typical working day. We define the load by both the total number of floors traveled, and the number of door-open events observed.

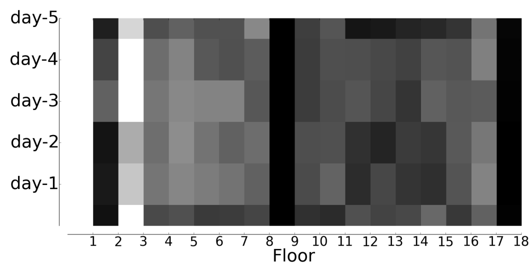

Figure 2. The number of door-open events at each floor over the five working days of a week. A lighter color indicates a higher number, whereas a darker color indicates a lower number.

the data from only one day, our observations are applicable to other working days as well. The figure shows that the overall load is not equally distributed among the elevators, in both metrics. This inequality is interesting, as it suggests that people tend to choose one of the two elevator groups. In our case, the office occupants tend to use elevators at the east side more (elevator #7 - #12). This observation suggests the dispatching algorithm should consider group-specific loads.

Next, we examine where elevators stop throughout the day. Each row in Figure 2 represents the load (or the number of door-open events) for one day, and the figure uses the color intensity to represent the frequency. Lighter color indicates a higher number, whereas a darker color indicates a lower number. An interesting observation is that a number of floors dominate the elevator usage. This observation is a supporting hint that parking idle elevators according to the history can reduce the average service wait time. We delve into this observation in the next subsection.

2.3 Temporal Analysis

Figure 2 presents the number of door-open events on a particular floor over five working days, and it shows several patterns. First, the relative frequency of door-open events is the same across all five days. For example, floors between 9 and 18 always have more door-open events than floors between 1 and 8. In addition, the fact that there is a pattern suggests that we can reuse historical data. Second, the frequency of door events is tied to the function of the floor. For example, both floor 1 and 3 have the most door-open events. The former is the entrance of the building, and the latter is a multi-purpose floor with cafeteria, cafes, library and gym.

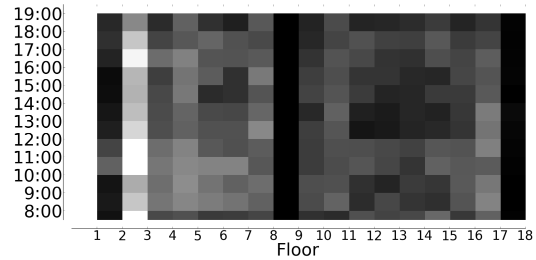

Figure 3. The number of door-open events at each floor over 12 hours on a working day. A lighter color indicates a higher number, whereas a darker color indicates a lower number.

On the other hand, floor 18 is a small-scale data center with a low count of occupants.

Next, we zoom in from the daily view into the hourly granularity. Specifically, Figure 3 divides one working day's data into 12 hourly windows (from 8AM to 8PM). The figure shows that it is rare to see a floor giving a constant load over time. In fact, many floors exhibit a cycle, which goes from low load to high load and then returns to low load at the end of the day.

3 Discussions and Future Work

While our real-world data set was collected from an office building, we acknowledge that it cannot represent all possible office buildings. In fact, the elevator usage patterns vary according to the building functions and layout, occupant types, etc. However, this paper aims to provide a first step towards tying elevator usage efficiency with human behavioral patterns.

Furthermore, we would like to comment on the kinds of buildings that can benefit from leveraging human behavioral patterns. Similar to other scheduling work, we believe the gain of adaptive approaches increases with the degree of freedom in the system. In other words, high-rise buildings with several elevators should benefit from leveraging human behavioral patterns. In low-rise buildings, since the elevators can quickly reach all floors, the reduction in service time is relatively small.

As part of the future work, we plan to build and deploy a human-centric elevator scheduling system that considers both human inputs and human behavioral patterns.

4 References

[1] American Council for an Energy-Efficient Economy. Opportunities for Elevator Energy Efficiency Improvements. 2005.

[2] National Elevator Industry, Inc. Elevator and Escalator Fun Facts. http://www.neii.org/presskit/printmaster.cfm?plink=NEII%20Elevator%20and%20Escalator%20Fun%20Facts.cfm.

[3] Otis Inc. ELEVONIC Class. http://www.otis.com/site/us/Pages/ElevonicClass.aspx, 2013.

[4] Schindler Inc. Personal Occupant Requirement Terminal (PORT). http://www.schindlerportna.com/keyfeatures/portterminal/, 2013.

[5] Slate. Energy and Elevators. http://www.slate.com/articles/health_and_science/the_green_lantern/2009/04/energy_and_elevators.html, 2009.

[6] The Wall Street Journal. The Ups and Downs of Making Elevators Go. http://online.wsj.com/article/SB10001424127887324469304578143200385871618.html, 2012.