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Modeling occupancy in single person offices

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Abstract

This paper examines the statistical properties of occupancy in single person offices of a large office building in San Francisco. A probabilistic model to predict and simulate occupancy in single person offices is proposed. It is found that vacancy intervals are exponentially distributed and that the coefficient of the exponential distribution for a single office could be treated as a constant over the day. Occupancy intervals are more complex than vacancy intervals. The distribution of occupancy intervals is time varying. Variations among different offices are examined. The implications of the findings on thermal and air quality control are discussed.

Keywords: Commercial buildings; Occupancy properties; Single person offices; Modeling

1. Introduction

It has been observed that offices in commercial buildings are vacant for a large percentage of the time during business hours. Bauman et al. [1] found that occupants were away from their offices 25–30% of the nominally occupied hours of the day.

Occupancy sensors are now commonly used for security applications and for lighting control. Occupancy sensor triggered lighting control has shown great potential to save electrical energy when offices are vacant. Jennings et al. [2], Maniccia et al. [3], and Richman et al. [4] reported electrical energy saving in a range of 3–45% in office rooms based on their field measurements.

The motivation for this study is to gain an understanding of how occupancy sensing can be used for thermal and/or air quality control in buildings. Using occupancy sensors, to control temperature or air quality, is complicated by the time lag required to return the temperature or air quality to an acceptable condition after or just before a space becomes re-occupied. Before we can use occupancy sensors for these purposes, it is necessary to understand, and be able to predict, the transient nature of occupancy during nominally occupied periods.

In this paper, we examine the statistical properties of occupancy in single person offices of a large office building in San Francisco. We propose a probabilistic model to predict and simulate occupancy in single person offices, and we discuss the implications of our findings on thermal and air quality control.

2. Methods

2.1. Occupancy data logs

The study uses the occupancy logs obtained from 35 single person offices at a large office building from 12/29/1998 to 12/20/1999. These data are taken from Jennings et al. [2] and Rubinstein et al. [5]. For each office, the data log contains a sequence of time-stamped events (occupied to vacant or vacant to occupied). The sensors operate by detecting motion, using an infrared sensor behind a fresnel lens. A vacant to occupied event occurs when the room is vacant and the sensor detects motion. An occupied to vacant event occurs when there has been no motion for a time interval that averaged 15 min for sensors used in this study.

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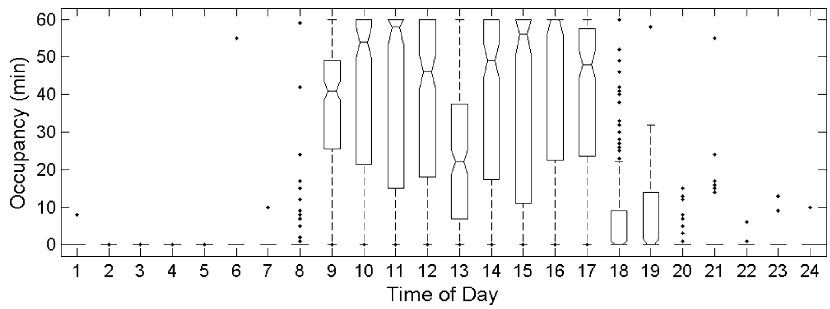

Fig. 1. Distribution of hourly occupied time over 24-h of day for an office.

Fig. 1 illustrates the distribution of hourly occupied time as a function of time of day for a randomly chosen office. The notch in the bar is the median. The bar contains the range between 25th and 75th quartiles. The whiskers extend to 1.5 times the inter-quartile difference from the 25th and 75th quartiles. The dots are outliers. There are three distinct levels in the hourly occupied time over the working hours. From 8:00 to 17:00 h, 75% of the time the office is occupied more than 25 min hourly except 12:00–13:00 h. There is no difference in occupancy ratio in the morning and afternoon. From12:00 to 13:00 h, 75% of the time office is occupied less than 38 min. This may be caused by the lunch break. From 17:00 to 19:00 h the office is occupied less than 10 min/h 75% of the time. This may be caused by the occupant, leaving work and then a scheduled, short activity, such as cleaning, occurs during that period of time. The median of hourly occupied time has two peaks over 24 h, one at 10:00–11:00 h and another at 15:00–16:00 h. During these two periods of time, 25% of the time the office is occupied full hour. The office is nominally occupied from 8:00–17:00 h.

Fig. 2 illustrates the distribution of the number of occupied to vacant events for a randomly chosen office in a day. It demonstrates that the occupant departs and arrives mostly five to six times a day. The probability with one depart a day is 8%. The frequency of departure and arrivals varies largely from day to day.

Figs. 3 and 4 illustrate the distribution of the length of occupancy and vacancy intervals for a randomly chosen office during the recorded period. The occupancy interval is

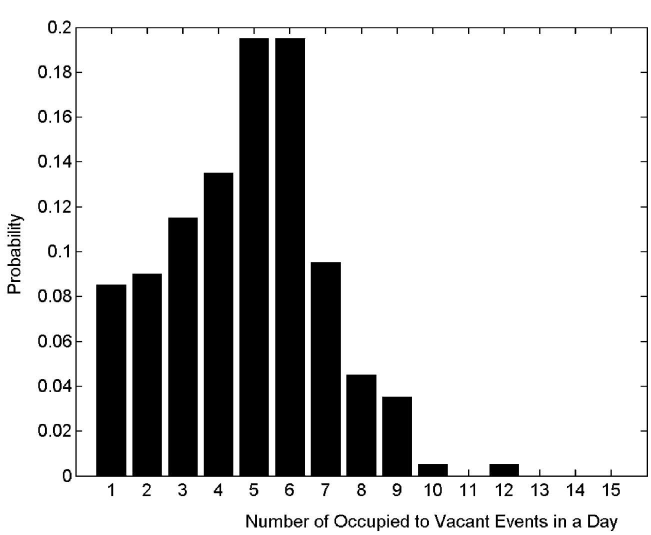

Fig. 2. Distribution of the number of occupied to vacant events for an office in a day.

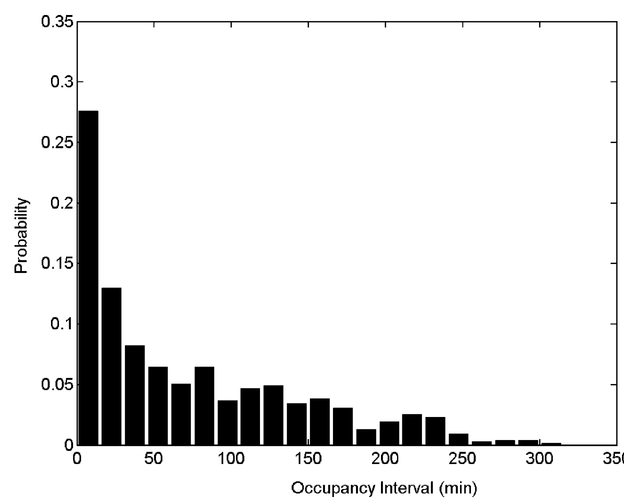

Fig. 3. Probability distribution of the occupancy intervals for an office.

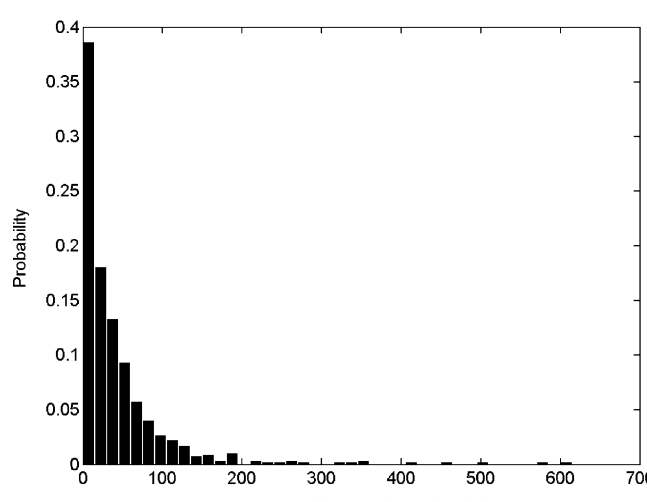

Fig. 4. Probability distribution of the vacancy intervals for an office.

reduced by 15 min to compensate for the 15-min delay in detecting an occupied-to-vacant event. It appears that shorter intervals occur more frequently than predicted for both occupancy and vacancy. Both distributions have long tails.

2.2. Modeling

We propose a non-homogeneous Poisson process model with two different exponential distributions to simulate the occupancy sequence in a single person office. The reasons for using such a model are, simplicity and the ability to explain the observed behavior.

We assume the occupancy and vacancy intervals of an occupant during business hours are independent and sequential random variables. This independence is tested by comparing the length of vacancy intervals and that of the preceding occupancy intervals with a rank-based non-parametric method. The Spearman's correlation coefficient is 0.1099, and the *P*-value under the null hypothesis that the correlation of two is zero is 0.003 [6]. The test indicates that there is a weak but statistically significant correlation between occupied intervals and vacancy intervals. The magnitude of the correlation is so small that we can ignore it. Fig. 5 visually displays the length of vacancy intervals versus that of the preceding occupancy intervals.

The intervals lengths are modeled as some exponentially distributed random variables. The parameters of the exponential distributions are estimated from the measured data, using the maximum likelihood estimation method. The model starts with a constant parameter for either occupancy or vacancy interval. If the constant parameter does not fit well, time-varying parameters are estimated and tested. The variation of the parameters among different offices is examined.

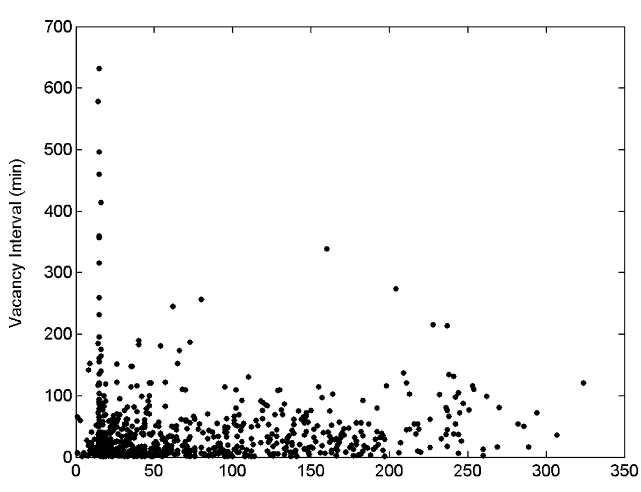

Fig. 5. Length of vacancy intervals compared with the preceding occupancy intervals.

3. Results

3.1. Parameter estimation

The lengths of occupancy and vacancy intervals are modeled from two independent exponential distributions. The density function of an exponential random variable is:

$$f(y) = [1/\beta]e^{-y/\beta}, \quad y > 0 \tag{1}$$

Maximum likelihood estimation method uses iterative weighted least square (IWLS) procedure to estimate the parameter β and its variance [7]. If the exponential model is correct, dispersion parameter ϕ should be 1. $\hat{\phi}$ is estimated from:

$$\hat{\phi} = \sum_{i=1}^{n}((y_i - \hat{\beta})/\hat{\beta})^2/(n-1) \tag{2}$$

For the length of occupancy interval of the above randomly chosen office: $\hat{\beta}_{\mathrm{occ}} = 72.8\,\mathrm{min}$, $\hat{\beta}_{\mathrm{occ}}$ is asymptotically normally distributed. Ninety-five percent confidence interval is (67.80, 77.93) $\hat{\phi}_{\mathrm{occ}} = 0.96$.

For the length of vacancy interval of the above randomly chosen office: $\hat{\beta}_{\mathrm{abs}} = 42.6\,\mathrm{min}$, $\hat{\beta}_{\mathrm{abs}}$ is asymptotically normally distributed. Ninety-five percent confidence interval is (39.58, 45.74) $\hat{\phi}_{\mathrm{abs}} = 2.13$, assess the goodness of fit.

The goodness of fit of the model is evaluated by the scaled deviance $D*(y;\hat{\beta})$. It is calculated as [7]:

$$D*(y;\hat{\beta}) = 2\sum_{i=1}^{n}\frac{\log(\hat{\beta}/y_i)}{\hat{\phi}}$$

If the model is correct, then the scaled deviance should have a chi-squared distribution with $n-1$ degree of freedom. In other words, the model is rejected when $D*(y;\hat{\beta}) > \chi^2_{n-1;1-\alpha}s$; we use $\alpha = 0.05$.

For the occupancy intervals of the above randomly chosen office: $D*(y;\hat{\beta})_{\mathrm{occ}} = 2853.5\} > \chi^2_{\mathrm{n}-1;1-\alpha} = 859.6228$, so the exponential distribution is rejected. For the vacancy intervals of the above randomly chosen office: $D*(y;\hat{\beta})_{\mathrm{abs}} = 516.8956 < \chi^2_{n-1;1-\alpha} = 797.0951$, so the exponential distribution is accepted, with some over dispersion.

Figs. 6 and 7 compare the fitted and observed frequencies of the lengths of the occupancy and vacancy intervals for the chosen room. Both exponential distributions fit better when the intervals last longer. They both underestimate the frequencies when the intervals last less than 15 min.

The false vacancy record may contribute to the underestimate of the frequency of short vacancy. When sensors are not able to detect motions of occupants, they record an occupied-to-vacant event, which causes the lights to shut off. If the room is actually occupied, the occupant may have to wave his hands or move around to turn on the light again. Such false vacancy and occupancy records are common in commercial motion-detecting occupancy sensors. They are not distinguishable from the normal events in the data set.

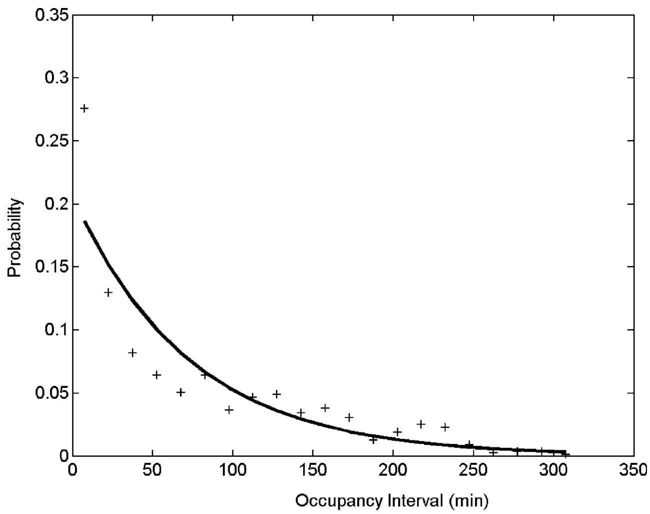

Fig. 6. Fitted and observed frequencies of the occupancy intervals.

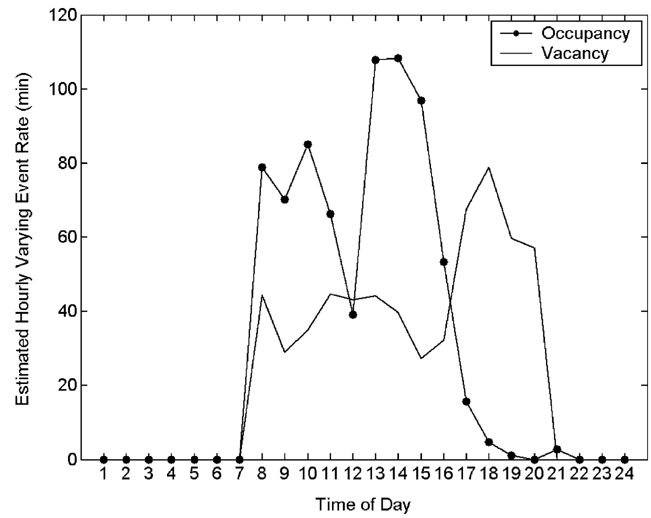

Fig. 8. Estimated hourly varying occupancy and vacancy rate (variation among different offices).

We checked whether or not the occupancy intervals were varying with time during the business hour. We fit the model of occupancy intervals in 1-h intervals of the day. The result is plotted in Fig. 8.

Fig. 8 shows that the occupancy intervals have a time-varying distribution. X-axis tick 1 corresponds to the time interval at 0.00–1.00 a.m., and so forth. Occupancy intervals may have three time varying parameters, as in the morning, lunch break, and afternoon. The estimated parameters range from 40 to 108 min. But even when the parameters are hourly varying, the only significant fits are intervals between 7:00–8:00, 11:00–12:00, and 20:00–21:00 h. Vacancy intervals may have two rate levels, one lasts around 40-min during most of the time of the working hour, another lasts 60–70 min at late afternoon after the normal night leaving time. All the parameters are significant except the one at 16:00–17:00 h interval.

We tested the non-homogeneous Poisson model on all 35 rooms. We found that the vacant intervals of all 35 rooms were exponentially distributed. The mean vacancy interval was different from room to room. When the mean vacancy intervals were allowed to vary hourly, the fits were improved at some hours, but not at all hours. The relationship between the estimated lengths of occupancy intervals versus the vacancy intervals for all offices is plotted in Fig. 9. One office has very long occupancy lasting 224 min and three other offices have very long vacancy lasting 111, 91, and 92 min. All other offices have averaged occupancy lasting 69 min and vacancy lasting 46 min. The mean vacancy interval is independent of the mean occupied interval.

As summarized in [5], the hourly occupancy rate shows three typical patterns from those offices. In the first office type, occupants usually leave the office during the middle of

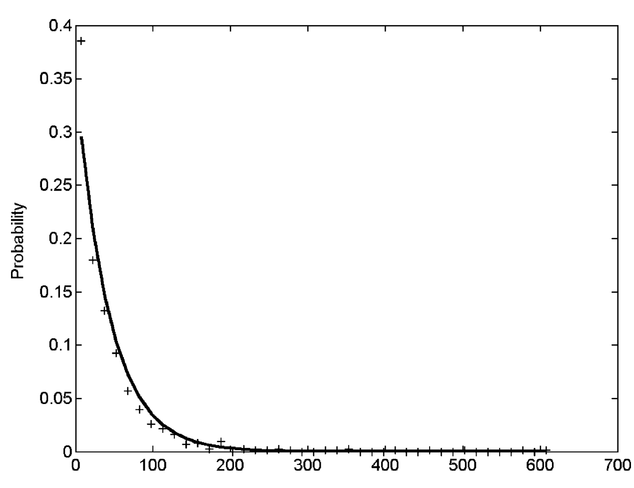

Fig. 7. Fitted and observed frequencies of the vacancy intervals.

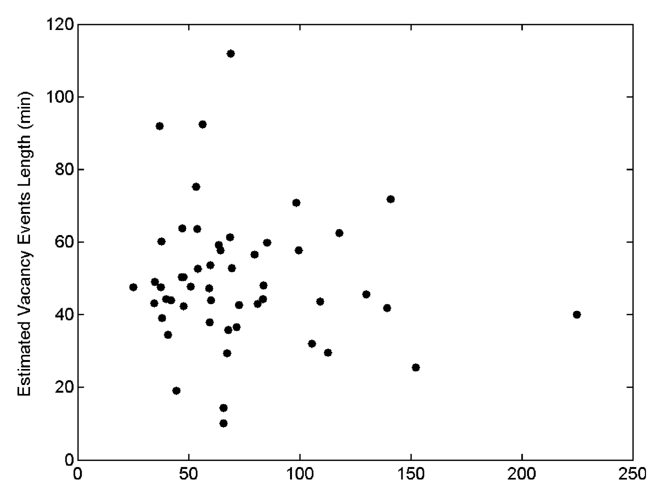

Fig. 9. Estimated lengths of occupancy intervals and vacancy intervals for 35 single person offices.

Table 1
Comparison of simulation and measurement

	Measurement	Simulation
Total analyzed days per year	171	171
Average occupied hour per day	6.17	6.47
Standard deviation	2.56	1.38
Average vacancy ratio per day	0.20	0.33
Standard deviation	0.16	0.13
Average depart and arrival per day	4.93	5.51
Standard deviation	2.06	1.36

the day, which is similar to the office in Fig. 1. In the second office type, occupants usually leave twice during the business day, once in the morning and once in the afternoon. In the third office type, occupants tend to stay in the office during the entire business day.

3.2. Simulation

The fitted two parameters (72.78, 42.60) of the occupancy and vacancy intervals are used to simulate the occupant pattern in single person offices. A few adjustments of the model are necessary in order to combine the clock-time information into the simulation. The morning arrival time is normally at 8:12 with a standard deviation of 11 min (mean is obtained after trimming outliers at 25th and 75th quartiles, standard deviation is estimated from 0.7 times the spread of the inter-quartile). The night leaving time is normally at 17:48 with a standard deviation of 79 min. To accommodate the low occupancy during 12:00–13:00 h, an independent normal random variable (mean, 12:30 and standard deviation, 15 min) is used to simulate the starting time of the lunch break.

The simulation runs as long as the days having the measurements. The statistics from the simulation and measurement are summarized in Table 1. The simulated occupancy rate per hour is plotted in Fig. 10.

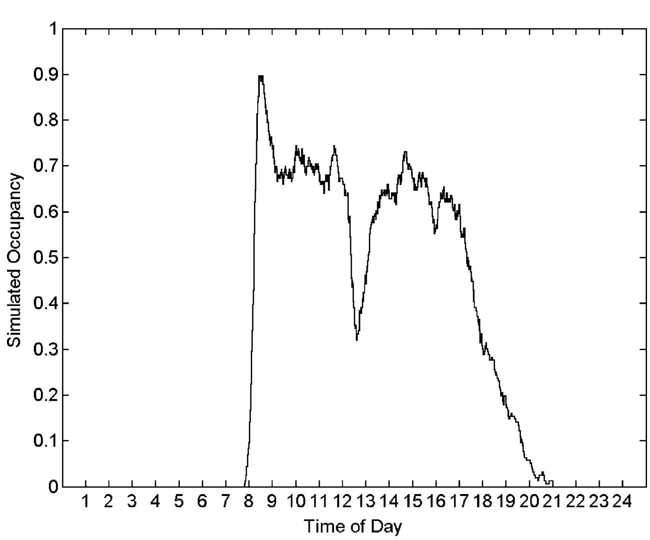

Fig. 10. Simulated hourly occupied rate as a function of time of day for a single office.

The simulation has a peak in the first hour, which Fig. 1 does not show. This peak is due to the assumption of the normal distribution of the morning arrival time. Using robust estimation, its standard deviation is very small. However, we find that the morning arrival time is not normally distributed. It has a small but very long right-hand (positive) tail. A more precise simulation of morning arrival time could be achieved by drawing samples from its empirical distribution, which this study did not do.

4. Discussion

People think that their comings and goings are deterministic, or they may work according to a schedule. But sensors observe random occupancy behavior. This randomness is similar to that in traffic movement naturally. Buses are operated according to schedules, but the arrival time of a bus at a stop is often modeled as a random process. Randomness is caused by variable traffic flow, weather, road condition, etc., and/or their combinations. Although, no similar studies have been carried out to observe people' movements in office buildings, one can guess that this random occupancy behavior may be obtained through multiple random factors and/or their random combinations.

It is found that the vacancy intervals are exponentially distributed but occupied intervals are not. These findings are not in conflict with each other. Compared to the vacancy intervals, the occupied intervals are more complex. A single motion sensor only records the largest time span of occupancy status in the room. If occupancy is caused by more than one occupant, then the sensor cannot tell when and how long, individual occupants arrive and stay. If the occupancy interval of each occupant were exponential, the recorded occupancy would be a complex mixture of more than one exponential distribution. This underlying occupancy interval structure is likely to cause the deficiency of an exponential model.

Using occupancy sensor to control temperature or air quality has a potential to save energy by applying an appropriate setback policy during business hours. The portion of saved energy would be close to the proportion of absent time by a simple first order approximation. But if the setback policy is too aggressive towards energy conservation, occupants may feel uncomfortable when they return. If the setback policy is too aggressive towards the comfort, there may be no adjustment at all during the vacancy, and therefore, waste energy. The occupancy model could help us to understand the transient nature of discomfort cost and the energy penalty associated with the variable re-arrival time.

The results reported here are derived from just one office building. It is possible that occupancy behavior in other buildings differs from that observed in this building.

5. Conclusion

The significant findings from this study are as follows:

1) The vacant intervals were exponentially distributed.
2) The exponential model was valid even when observing individual offices.
3) The mean vacant interval varied from office to office.
4) The exponential model was not validated for occupied intervals.
5) A (time-varying) model fit the occupied intervals better, but some intervals still did not pass the goodness-of-fit test.

Acknowledgements

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