

# Dienstleistungsmanagement

## Übung 5

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# Besprechung Übungsblatt 4



# Time Series Models: N-Period Moving Average

Example: Forecast for occupancy rate of a hotel on Saturdays for September 12

Saturday	Date	Period	Occupancy (A)	3-Period Moving Average	Forecast (F)
August	1	1	79		
August	8	2	84		
August	15	3	83	82	
August	22	4	81	83	82
August	29	5	98	87	83
September	5	6	100	93	87
September	12	7			93

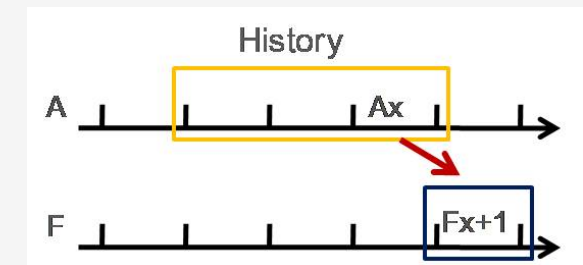
Moving Average Period 3:

$$MA_3 = \frac{83 + 84 + 79}{3} = 82$$

Moving Average Period 4:

$$MA_4 = \frac{81 + 83 + 84}{3} = 83$$

Moving Averages are taken to forecast the occupancy rate for new period.



(Fitzsimmons & Fitzsimmons, 2011)



$$MA_t = \frac{A_t + A_{t-1} + A_{t-2} + \dots + A_{t-N+1}}{N}$$

Annahme:  $N = 3$

Moving Average Juli:  $(26 + 27 + 23)/3 = 25,33$  (25 Packungen)

Bitte immer den Rechenweg und die Formel aufschreiben!



**Exponential smoothing:** Used e.g., for demand forecasting, Based on N-period moving average

- Accidental increases or decreases in the average are “smoothed out” (extreme values weight less for forecasting of following periods): Advantage compared to other methods
- Old data is kept in calculation, but influence is reduced steadily
- “Defensive” forecasting method: Forecasting values often lower than actual values

Forecast error of the previous period is put back in next period

$A_t$  = Actual observed value for current period t

$S_t$  = Smoothed value for current period t

$S_{t-1}$  = Smoothed value for previous period

$(A_t - S_{t-1})$  = Forecast error of previous period (Difference of actual and smoothed value of previous period)

$\alpha$  = Smoothing constant; between 0 and 1 (fraction of the forecast error that is added to smoothed value of previous period)

Smoothing value for current period:  $S_t = S_{t-1} + \alpha(A_t - S_{t-1})$

(Fitzsimmons & Fitzsimmons, 2011)



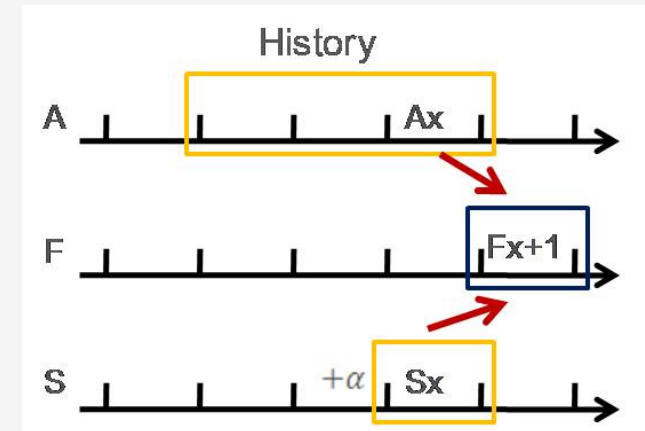
Smoothed value of period  $t$ : Used as forecast for following period  $t+1$

$F_{t+1}$  = Forecast for following period  $t+1$

$F_{t+1} = S_t$  (Rounded to an integer)

Smoothed value of period  $t$ :

$$S_t = \alpha(A_t) + (1 - \alpha)S_{t-1}$$



(Fitzsimmons & Fitzsimmons, 2011)



# Time Series Models: Exponential Smoothing: Simple Exponential Smoothing

Saturday	Date	Period	Actual Occupancy	Smoothed Value	Forecast	Error
		$t$	$A_t$	$S_t$	$F_t$	$A_t - F_t$
August	1	1	79	79,00		
August	8	2	84	81,50	79	5
August	15	3	83	82,25	82	1
August	22	4	81	81,63	82	-1
August	29	5	98	89,81	82	16
September	5	6	100	94,91	90	10

(Fitzsimmons & Fitzsimmons, 2011)



Alpha = 0,1

Periode 2:  $F_2 = S_1 = A_1$

Periode 3:  $F_3 = S_2$  (gerundet auf ganze Zahl)

Berechnung geglätteter Wert:  $S_t = \alpha(A_t) + (1 - \alpha)S_{t-1}$

$S_2 = 0,1 * 18 + 0,9 * 15 = 15,3$

$F_3 = 15,3$  runden = 15

Monat	Periode	Tatsächlicher Wert	Geglätteter Wert	Prognose	Fehler
	t	$A_t$	$S_t$	$F_t$	$A_t - F_t$
Januar	1	15	15		
Februar	2	18	15,3	15	3
März	3	22	15,97	15	7
April	4	23	16,67	16	7
Mai	5	27	17,71	17	10
Juni	6	26	18,54	18	8
Juli	7			<b>19</b>	



Alpha = 0,5

Periode 2:  $F_2 = S_1 = A_1$

Periode 3:  $F_3 = S_2$  (gerundet auf ganze Zahl)

Berechnung geglätteter Wert:  $S_t = \alpha(A_t) + (1 - \alpha)S_{t-1}$

$S_2 = 0,5 * 18 + 0,5 * 15 = 16,5$

$F_3 = 16,5$  runden = 17

Monat	Periode	Tatsächlicher Wert	Geglätteter Wert	Prognose	Fehler
	t	$A_t$	$S_t$	$F_t$	$A_t - F_t$
Januar	1	15	15		
Februar	2	18	16,5	15	3
März	3	22	19,25	17	5
April	4	23	21,13	19	4
Mai	5	27	24,06	21	6
Juni	6	26	25,03	24	2
Juli	7			<b>25</b>	



## **Einfluss der Alpha-Werte:**

Stellt dar, wie stark Schwankungen des tatsächlichen Wertes beim geglätteten Wert und somit bei der Prognose für die nächste Periode berücksichtigt werden.

Niedriger Wert für Alpha: Aktuelle Schwankungen werden weniger stark berücksichtigt. Diese haben somit weniger Einfluss auf die Prognose.

Hoher Wert für Alpha: Aktuelle Schwankungen werden stärker berücksichtigt. Diese haben somit einen größeren Einfluss auf die Prognose.

Wahl des Alphas: Abhängig davon, wie stark man aktuelle Schwankungen in die Prognose miteinbeziehen will (Trade-off). Basiert in der Praxis auf Erfahrungen.



# Time Series Models: Exponential Smoothing: Trend Adjustment

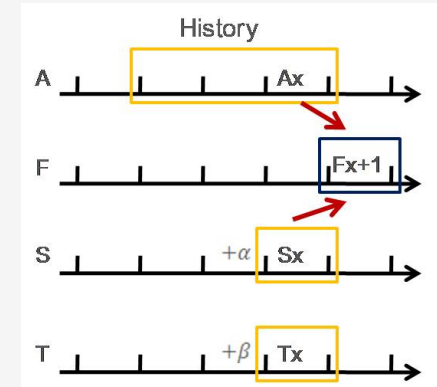
**Trend:** Average of change when comparing observed values of previous and actual periods over time

Trend value is added to smoothed value equation:

$T_{t-1}$  = Smoothed trend value of previous period

$T_t$  = Smoothed trend value of current period

$\beta$  = Smoothing constant (between 0 and 1)



New equation of  $S_t$  including smoothed trend value:  $S_t = \alpha(A_t) + (1 - \alpha)(S_{t-1} + T_{t-1})$

Smoothed trend value of current period:  $T_t = \beta(S_t - S_{t-1}) + (1 - \beta)T_{t-1}$

Forecast:

$$F_{t+1} = S_t + T_t \quad (\text{Rounded})$$



# Time Series Models: Exponential Smoothing: Trend Adjustment

## Example

Week	Actual Load Factor	Smoothed Value	Smoothed Trend	Forecast	Forecast Error
$t$	$A_t$	$S_t$	$T_t$	$F_t$	$ A_t - F_t $
1	31	31,00	+ 0,00		
2	40	35,50	+ 1,35	31	9
3	43	39,93	2,27	37	6
4	52	47,10	3,74	42	10
5	49	49,92	3,47	51	2
6	64	58,69	5,06	53	11
7	58	60,88	4,20	64	6
8	68	66,54	4,63	65	3

Blue arrows indicate the forecast for week 2 is 31 and for week 3 is 37.

(Fitzsimmons & Fitzsimmons, 2011)



Alpha = 0,1, Beta = 0,2

Periode 2:  $F_2 = S_1 + T_1$

Periode 3:  $F_3 = S_2 + T_2$  (gerundet auf ganze Zahl)

Berechnung geglätteter Wert:  $S_2 = 0,1 \cdot 18 + 0,9 \cdot (15 + 0) = 15,3$

Berechnung Trend:  $T_2 = 0,2 \cdot (15,3 - 15) + 0,8 \cdot 0 = 0,06$

Forecast:  $F_3 = 15,3$  runden = 15

$$S_t = \alpha(A_t) + (1 - \alpha)(S_{t-1} + T_{t-1})$$

$$T_t = \beta(S_t - S_{t-1}) + (1 - \beta)T_{t-1}$$

Monat	Periode	Tatsächlicher Wert	Geglätteter Wert	Geglätteter Trend	Prognose	Fehler
	t	$A_t$	$S_t$	$T_t$	$F_t$	$ A_t - F_t $
Januar	1	15	15	0		
Februar	2	18	15,3	0,06	15	3
März	3	22	16,02	0,19	15	7
April	4	23	16,89	0,33	16	7
Mai	5	27	18,20	0,53	17	10
Juni	6	26	19,46	0,68	19	7
Juli	7	28	20,93	0,84	<b>20</b>	8
August	8				<b>22</b>	



# Aufgabe Overbooking



# Managing Demand: Reservation Systems and Overbooking

**Overbooking** of capacity (e.g., hotel rooms, airplane seats): Selling more seats than total capacity and expecting no-shows

Problems of overbooking:

- If overbooked capacity  $>$  number of no-shows:
  - Customers with reservation must be turned away
  - Costs of overbooking: Reimbursement of denied customers
- Overbooking strategy:
  - Minimization of opportunity costs of empty capacity
  - Minimization of costs of passengers with reservation being turned away





# Managing Demand: Reservation Systems and Overbooking

## Calculation of optimal number of overbookings

- $d$  = Number of no-shows
- $P(d)$  = Probability of a no-show
- $x$  = Number of reservations overbooked
- $P(d < x)$  = Cumulative probability of a no-show

Example: Hotel wants to calculate the loss per night for different numbers of overbooking & no-shows and the optimal number of overbookings

- No-show loss: Loss of contribution for empty room: € 40 p.n.
- Overbooking loss: Penalty costs for guests sent away (need to stay in another hotel): € 100 p. denied guest

No-shows $d$	Probability $P(d)$	Reservations overbooked $x$	Cummulative probability $P(d < x)$
0	0,07	0	0
1	0,19	1	0,07
2	0,22	2	0,26
3	0,16	3	0,48
4	0,12	4	0,64
5	0,10	5	0,76
6	0,07	6	0,86
7	0,04	7	0,93
8	0,02	8	0,97
9	0,01	9	0,99

(Fitzsimmons & Fitzsimmons, 2011)



# Managing Demand: Reservation Systems and Overbooking

$$\begin{aligned} \text{Expected number of no-shows} &= \sum d * P(d) \\ &= 0 * 0,07 + 1 * 0,19 + 2 * 0,22 + \dots + 9 * 0,01 = 3,04 \end{aligned}$$

Expected opportunity loss (loss of contribution for empty room due to no-show) =  
Expected number of no-shows \* no-show loss  
 $3,04 * € 40 = € 121,60$  p.n.

Avoid some of this loss with overbooking: However: Penalty for guests sent away  
(if higher number of overbookings than number of no-shows)

- No-show loss: € 40 p.n.
- Overbooking loss: € 100 p. denied guest

Diagonal: Number of no-shows & number of overbookings are the same (no loss: win-win situation)



# Managing Demand: Reservation Systems and Overbooking

## Loss due to overbookings

		Reservations overbooked (overbookings)									
No-shows	Probability	0	1	2	3	4	5	6	7	8	9
0	0,07	0	100	200	300	400	500	600	700	800	900
1	0,19	40	0	100	200	300	400	500	600	700	800
2	0,22	80	40	0	100	200	300	400	500	600	700
3	0,16	120	80	40	0	100	200	300	400	500	600
4	0,12	160	120	80	40	0	100	200	300	400	500
5	0,1	200	160	120	80	40	0	100	200	300	400
6	0,07	240	200	160	120	80	40	0	100	200	300
7	0,04	280	240	200	160	120	80	40	0	100	200
8	0,02	320	280	240	200	160	120	80	40	0	100
9	0,01	360	320	280	240	200	160	120	80	40	0
<b>Expected loss</b>	(--)	121,60	91,40	87,80	115,00	164,60	231,00	311,40	401,60	497,40	560,00

(Fitzsimmons & Fitzsimmons, 2011)



# Managing Demand: Reservation Systems and Overbooking

Expected loss per number of no-shows and overbookings:

Sum: Expected loss per certain number of no-shows & overbookings \* Probability

E.g., total expected loss for 2 reservations overbooked:

$$= 0,07 * € 200 + 0,19 * € 100 + 0,22 * € 0 + 0,16 * € 40 + 0,12 * € 80 + 0,10 * € 120 \\ + 0,07 * € 160 + 0,04 * € 200 + 0,02 * € 240 + 0,01 * € 280 = € 87,80$$

Optimum number of overbookings: Number which minimizes expected loss:

2 overbookings (loss: € 87,80)

Expected gain p.n. from overbooking: Expected loss without overbooking – Expected loss optimum  
number of overbookings

$$€ 121,60 - € 87,80 = € 33,80$$



# Managing Demand: Reservation Systems and Overbooking

Critical fractile criterion (to identify best overbooking strategy):

- $d$  = number of no-shows
- $x$  = number of rooms overbooked
- $C_u$  = lost room contribution when customer does not keep his reservation (underestimation of number of no-shows)
- $C_o$  = opportunity loss when no room is available for an overbooked guest (overestimation of number of no-shows)

$$P(d < x) \leq \frac{C_u}{C_u + C_o}$$

$$P(d < x) \leq \frac{\text{€ } 40}{\text{€ } 40 + \text{€ } 100} \leq 0,286$$

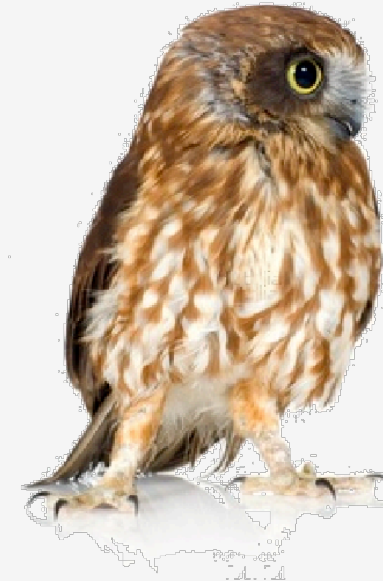
The next cumulative probability below 0,286 is 0,26 for overbooking of 2 rooms (optimal number of overbookings: 2 )



# Managing Demand: Reservation Systems and Overbooking

No-shows $d$	Probability $P(d)$	Reservations overbooked $x$	Cummulative probability $P(d < x)$
0	0,07	0	0
1	0,19	1	0,07
2	0,22	2	0,26
3	0,16	3	0,48
4	0,12	4	0,64
5	0,1	5	0,76
6	0,07	6	0,86
7	0,04	7	0,93
8	0,02	8	0,97
9	0,01	9	0,99

(Fitzsimmons & Fitzsimmons, 2011)



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