Forecasting CPU usage of Virtual Machines

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I. Introduction

In this paper we forecast CPU usage by five different virtual machines by using different such as moving average (MA), weighted moving average (WMA), exponential Smoothing(ES), and exponential Smoothing with trend (EST). Along with these basic methods, we also tested moving window regression models.

To test the performance of the forecasting methods we used tracking signal ratio (TS). Tracking signal is the ratio of cumulative sum of forecasting signals to the mean absolute deviation. Which indicates the presents of bias in the results produced by the forecast model.

$$TS = \frac{\sum A_t - F_t}{MAD} \tag{1}$$

Where A_t is the actual value, F_t is predicted value and MAD is the mean absolute deviation.

$$MAD = \frac{\sum |A_t - F_t|}{n} \tag{2}$$

For a better forecasting model, TS should be not grater than 4 and not less than -4.

$$-4 < TS < +4 \tag{3}$$

If tracking signal value is out the limits, then the forecasting model should be re-evaluated. If the TS above 4, most of our predictions as above actual values and vice verse.

II. Forecasting Techniques

A. Moving Average (MA)

In this technique, the forecasting is done by taking the simple average of last n data. i.e., to predict at time t we take the mean of values from $t - n$ to $t - 1$ as shown in the equal below.

$$F_t = \frac{\sum_{i=1}^{n} A_{(t-i)+1}}{n}, n \leq d \tag{4}$$

Where, F_t is the predicted value, A_t are the actual values and window size n should be less than or equal to the total size of the data d.

As this is a simple averaging of last n values, this method is computationally simple. However, if there is a lot of variation in the data, this method lags behind the data and produces lot of deviation.

In this paper to test the performance of the moving average method we choose window sizes of $\{3, 5, 9, 11, 20\}$.

B. Weighted Moving Average (WMA)

Similar to moving average technique, in this method we predict using the last n values. But, instead of given same weights to all the values we assign different weights based on the effect of value will be on the final prediction. In this method one thing to note is that the sum of all the weights should be equal to 1.

$$F_t = \sum_{i=1}^{n} W_i * A_{(t-i)+1}, n \leq d \tag{5}$$

Where, F_t is the predicted value, W_i are the weights whose some equals to 1 ($\sum_{i=1}^{n} W_i = 1$), A_t are the actual values and window size n should be less than or equal to the total size of the data d.

Performance of this method mainly depends on the weights and window parameters. In this paper, as CPU utilization data is collected every 5 min, if the utilization increases there is steep increase or vice verse. So, it is better to have more weight to the latest value in time series than to the old value. To test the performance we use same window sizes as above and for weight simple linear increments is used. i.e., if the window size is 5 then weights are assigned as $\left\{\frac{1}{1}, \frac{1}{2}, \frac{1}{3}, \frac{1}{4}, \frac{1}{5}\right\}$.

C. Exponential Smoothing (ES)

In exponential smoothing the weight to the past predictions is given in exponentially decreasing manner. Unlike moving average method, where all the n values get equal weights, this method gives exponentially reducing weights and discounted the past data in a more gradual manner [1].

If a is the smoothing constant, F_t and A_t are predicted and actual values, then exponential smoothing is given as:

$$F_t = a * A_{t-1} + (1 - a) * F_{t-1} \tag{6}$$

To test the performance of this method we use a values of $\{0.2, 0.4, 0.6, 0.8\}$. If a value is close to 1, then more weight is given to the latest actual value and less weight to the last predicted value. Exponential smoothing produces the results by taking interpolation between latest actual value and last predicted value [1].

D. Exponential Smoothing with Trend (EST)

The main disadvantage of exponential smoothing (ES) is that it does not follow the trend [2]. To overcome this double exponential smoothing or exponential smoothing with trend (EST) is proposed.

If FIT_t is the predicted value with trend, T_t is the trend for current predicting, then exponential smoothing with trend is given as:

$$FIT_t = F_t + T_t \tag{7}$$

$$F_t = a * A_{t-1} + (1 - a) * FIT_{t-1} \tag{8}$$

$$T_t = T_{t-1} + d(F_t - FIT_{t-1}) \tag{9}$$

Where, a and b are the prediction smoothing and trend smoothing constants.

For performance testing of exponential smoothing with trend same a values are used and $d = 0.5$.

E. Moving Window Regression (MWR)

Regression is statistical technique used to estimate the relation among variables [3]. This method follows the same technique as moving average, instead of taking the average of the values in given window we fit a polynomial line and predict the value.

To test the performance of the moving window regression, same window sizes as moving average are selected and 1st (linear regression) and 2nd order polynomial equations are used.
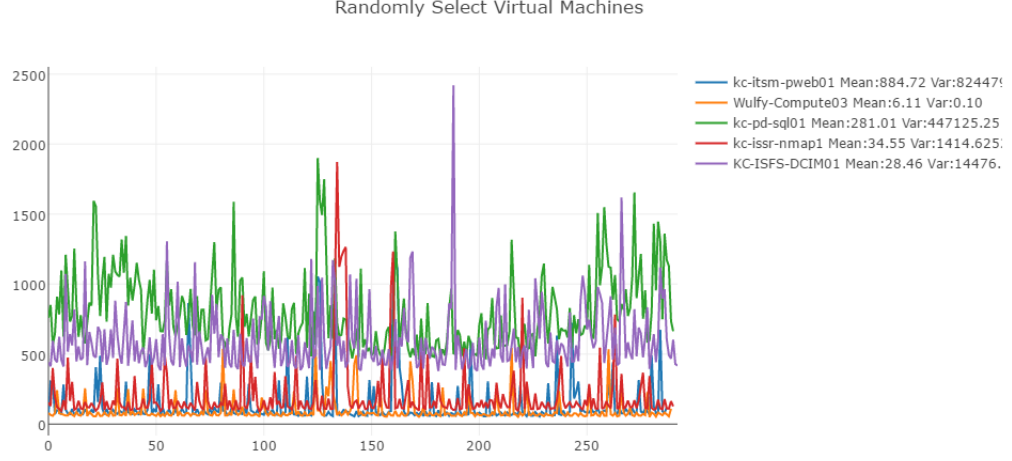
Fig. 1.   Randomly selected virtual machines, their mean and variance

III.   EXPERIMENTS

A. Dataset

The CPU utilization data is collected from UMKC datacenter at an intervals of $5min$ for total of 506 virtual machines. For each virtual machine CPU utilization(MHz) is collect at $5min$ intervals for $24hrs$, generating average of 284 values. For the evaluation purpose instead of considering all the virtual machines only 5 are considered randomly.

From Figure - 1, it can seen that except virtual machine $Wulfy - Compute03$ all the other virtual machines have very high variance, which results in constantly varying values and predicting these virtual machine CPU utilization will be really difficult.

The performance of each forecasting method is tested using mean absolute deviation (MAD) and tracking signal ratio (TS) as explained in section-I. For the forecasting method to perform better its mean absolute deviation should be close to zero and its tracking signal to be between -4 and +4.
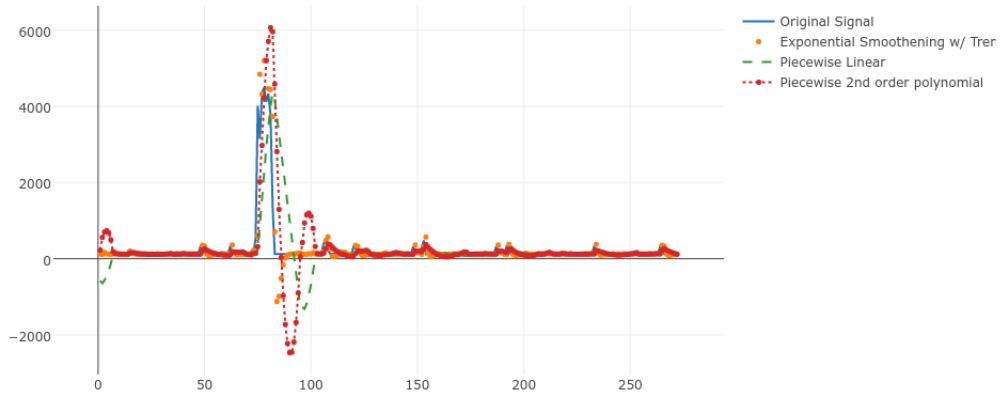
Fig. 2.   Large trend effect on prediton using exponential smoothong with trend, moving window regression methods.

B. Results

In table-I mean absolute deviation(MAD) and tracking signal ratio (TS) are produced for all the virtual machines with different forecasting techniques.

	kc-itsm-pweb01		Wulfy-Compute03		kc-pd-sql01		kc-issr-nmap1		KC-ISFS-DCIM01	
Moving Average										
Window Size	TS	MAD	TS	MAD	TS	MAD	TS	MAD	TS	MAD
3.00	-6.60	315.62	-2.24	0.15	-41.76	99.40	-0.06	20.81	0.00	16.95
5.00	-3.89	318.02	-7.76	0.15	-48.52	135.29	0.25	21.31	0.08	20.50
9.00	-11.69	336.98	-8.12	0.16	-30.82	175.56	0.70	21.48	0.08	26.13
11.00	-16.02	338.30	-6.39	0.17	-23.61	184.84	-0.96	20.04	0.10	27.73
20.00	-19.29	358.36	-1.58	0.19	-11.14	207.24	1.06	21.14	0.10	31.58
Weighted Moving Average										
Window Size	TS	MAD	TS	MAD	TS	MAD	TS	MAD	TS	MAD
3.00	-6.25	314.91	-1.15	0.14	-41.61	85.99	-0.07	20.31	-0.02	14.62
5.00	-2.04	308.93	-7.22	0.15	-47.22	110.18	0.16	20.72	0.07	17.41
9.00	-9.05	313.74	-5.33	0.15	-22.32	135.49	0.33	21.18	0.07	21.68
11.00	-12.09	316.24	-3.54	0.16	-13.95	145.53	-1.42	20.82	0.09	23.61
20.00	-12.37	331.37	-0.43	0.18	-3.19	177.61	0.50	20.90	0.10	28.70
Exponential Smoothing										
a value	TS	MAD	TS	MAD	TS	MAD	TS	MAD	TS	MAD
0.20	-17.70	325.31	-28.29	0.18	-33.86	173.62	1.02	19.93	0.19	21.90
0.40	-8.70	311.55	-16.01	0.16	-25.43	116.54	0.20	19.93	0.08	16.60
0.60	-5.83	319.04	-11.17	0.15	-22.27	88.89	0.06	19.77	0.05	13.45
0.80	-4.64	336.73	-8.52	0.15	-19.75	75.11	0.01	19.75	0.02	11.26
Exponential Smoothing with Trend										
a value	TS	MAD	TS	MAD	TS	MAD	TS	MAD	TS	MAD
0.20	5.16	373.62	0.32	0.21	-0.63	255.11	-0.30	25.80	1.86	34.66
0.40	0.81	358.03	0.16	0.19	-0.25	152.81	-0.31	27.27	-0.03	20.14
0.60	-0.19	373.95	-0.01	0.18	0.04	114.20	-0.10	26.17	-0.06	15.24
0.80	-1.11	405.86	0.00	0.19	0.04	98.42	-0.11	25.99	-0.07	14.80
Moving window Regression 1st order polynomial										
Window Size	TS	MAD	TS	MAD	TS	MAD	TS	MAD	TS	MAD
3.00	-2.92	479.21	3.11	0.21	-7.17	99.59	-0.07	32.39	-0.12	16.03
5.00	3.91	384.22	-3.24	0.19	-3.91	112.45	-0.13	29.46	0.01	17.06
9.00	0.57	334.49	3.26	0.18	24.87	142.35	-0.52	28.43	-0.02	22.77
11.00	0.96	341.35	4.62	0.18	25.04	161.19	-2.04	27.58	0.03	26.29
20.00	7.46	323.71	2.23	0.20	16.32	212.39	-0.74	23.82	0.05	34.56
Moving window Regression 2nd order polynomial										
Window Size	TS	MAD	TS	MAD	TS	MAD	TS	MAD	TS	MAD
3.00	-2.10	1124.95	-1.80	0.56	5.29	198.19	-0.05	73.65	-0.09	23.23
5.00	-0.82	599.81	-5.10	0.31	4.61	138.66	-0.03	47.43	0.08	21.20
9.00	-1.78	416.08	3.30	0.23	13.10	138.94	0.21	37.86	-0.13	24.52
11.00	0.19	381.49	1.60	0.23	0.63	153.50	0.01	34.34	-0.07	26.34
20.00	10.10	365.91	-1.71	0.21	-13.25	211.96	0.61	27.42	-0.02	34.92

TABLE I. PERFORMANCE OF DIFFERENT FORECASTING METHODS FOR RANDOMLY SELECTED FIVE VIRTUAL MACHINES

From table-I, it can be seen that exponential smoothing with trend produced better performance with very good tracking signal ratio (TS) compared any other method. Virtual machine 'Wullfy-Compute03' due vary less variance through the data it achieved vary less mean absolute deviation through all the forecasting methods.

In case of moving average and weighted moving average forecasting methods, the performance is not consistent across all the tested virtual machines. virtual machines $kc-itsm-pweb01, kc-pd-sql01, and KC-ISFS-DCIM01$ achieved better performance with small window size. Whereas, $kc-issr-nmap1$ and $Wulfy-Compute03$ achieved better performance as the window size is increased.

Except for $kc-itsm-pweb01$ all the virtual machines achieved better performance as the a values is increased in both exponential smoothing and exponential smoothing with trend. In these two, exponential smoothing with trend achieved better performance.

From both regression results it can be seen that the performance totally depends on the variation in the data. In both cases it can be seen in table-I that except for last two virtual machines the mean absolute deviation reduced as the window size is increased. If there is a sudden change in the data, especially for smaller window and almost all cases of 2nd order polynomial regression, the prediction goes way off the data. If these is a huge negative trend, then there is a chance for prediction to be in negative values. This can also be seen in case of exponential smoothing with trend as shown in figure-2.

IV. CONCLUSION

In paper we used different types of forecasting techniques including simple forecasting techniques such as moving average, weighted moving average, exponential smoothing and exponential smoothing with trend. Along with these a moving window regression technique is also used to forecast CPU utilization by different virtual machines in UMKC datacenter. Out of all forecasting methods exponential smoothing with trend achieved better performance than other method. However, if there is a large trend in the data, the prediction using this method is far away from actual value. So, there is no one better method to use on all the virtual machine. It is better to create a method from combination of these methods or use different forecasting techniques.

References

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