

EENG 581: Power System Operation and Management**HW3: Load Forecast**

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Learning Objectives:

- Develop linear models to forecast the demand.
- Use the WLS technique to solve a linear demand forecast model.
- Use the correlation technique to solve a linear demand forecast model.

1. The historical data of the annual peak demand for an electric utility are given below. Model the peak demand using the linear regression technique (i.e., assume $d(t) = a + b \cdot t$) and find a forecast for demand at year 6. Clearly, report the values of parameters a and b .

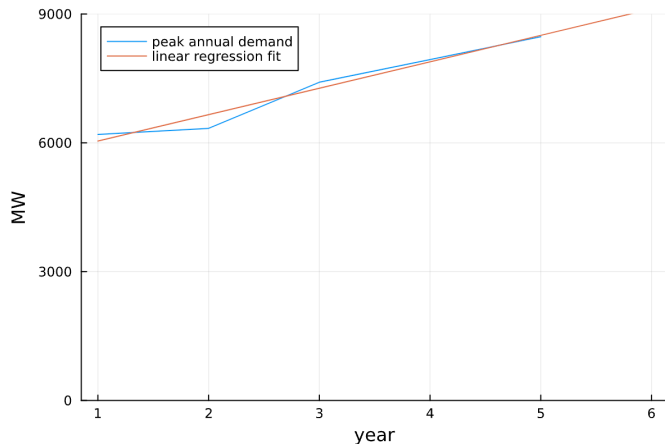
Year	1	2	3	4	5
Peak Annual Demand (MW)	6,197	6,337	7,411	7,940	8,473

2. Suppose that we have a linear demand model similar to the one considered in the previous problem. We are now going to solve the problem using WLS state estimation. Here, our states (unknowns) are the coefficients of the linear model, i.e., coefficients a and b . Demand values for previous years are then considered as the measurements. This gives us a measure model of the form: $d(t) = a + b \cdot t + e(t)$. Use the WLS technique to find coefficients a and b , and then use the model to find the forecasted demand at year 6. Solve this model twice: first assuming that all previous year measurements have the same weight (accuracy), and a second time, assuming that the weight associated with year t is $w(t) = 0.7^{(T-t)}$, where T is 5. Notice how the latter assigns a larger weight (importance) to more recent measurements.
3. For problem 1 assume a Markov model of the form $d(t) = a \cdot d(t-1) + e(t)$. Find coefficient a using the correlation method. Determine the demand forecast for years 6 and 7.
4. The peak load data for a utility company is given in the table below. Assume that only the load data for years 1981–1988 is available. Using this data, derive a time-series linear model for the peak demand based on its four past values, i.e. demand at year t is a linear function of demands of the previous four years. Use the model and its estimated load values to predict the demand for years 1989–1996. Compare with the actual values provided in the table below.

Year	Peak Load (GW)
1981	3,179
1982	3,694
1983	3,981
1984	4,672
1985	5,158
1986	5,361
1987	5,803
1988	6,152
1989	6,279
1990	6,664
1991	7,004
1992	7,215
1993	7,503
1994	7,657
1995	8,149
1996	8,491

1. The historical data of the annual peak demand for an electric utility are given below. Model the peak demand using the linear regression technique (i.e., assume $d(t) = a + b \cdot t$) and find a forecast for demand at year 6. Clearly, report the values of parameters a and b .

Year	1	2	3	4	5
Peak Annual Demand (MW)	6,197	6,337	7,411	7,940	8,473



forecasted peak demand in year 6: 9118 MW

	Coef.
(Intercept)	5425.1
year	615.5

in $d(t) = a + bt$

$= a$
 $= b$

```
1 using DataFrames, GLM, StatsModels
2 using Statistics
3 using Plots
4
5 demand_column_name = "peak annual demand MW"
6 demands = [6197, 6337, 7411, 7940, 8473]
7 df = DataFrame(year=1:5, d=demands)
8 years = df[!, "year"]
9
10 plot(years, df[!, "d"],
11       label="peak annual demand",
12       ylabel="MW",
13       xlabel="year",
14       ylims=[0, 9000]
15 )
16
17 ols = lm(@formula(d ~ year), df)
18
19 d_predicted = predict(ols, DataFrame(year=1:6))
20 plot!(1:6, d_predicted, label="linear regression fit")
21
22 println(coef(ols))
23 println("forecasted peak demand in year 6: $(round(Int, d_predicted[6])) MW")
24
25 # OR, if we were meant to do this more by hand...
26 x = years
27 y = demands
28 x_mean = mean(x)
29 y_mean = mean(y)
30 N = length(years)
31
32 slope = sum((x[i] - x_mean) * (y[i] - y_mean) for i in 1:N) / sum((x[i] - x_mean)^2 for i in 1:N)
33 intercept = y_mean - slope * x_mean
```

2. Suppose that we have a linear demand model similar to the one considered in the previous problem. We are now going to solve the problem using WLS state estimation. Here, our states (unknowns) are the coefficients of the linear model, i.e., coefficients a and b . Demand values for previous years are then considered as the measurements. This gives us a measure model of the form: $d(t) = a + b \cdot t + e(t)$. Use the WLS technique to find coefficients a and b , and then use the model to find the forecasted demand at year 6. Solve this model twice: first assuming that all previous year measurements have the same weight (accuracy), and a second time, assuming that the weight associated with year t is $w(t) = 0.7^{(T-t)}$, where T is 5. Notice how the latter assigns a larger weight (importance) to more recent measurements.

$$x = \begin{bmatrix} a \\ b \end{bmatrix} \longrightarrow \text{states}$$

$$z = \begin{bmatrix} \text{demand}(1) \\ \vdots \\ \text{demand}(5) \end{bmatrix} \longrightarrow \text{measurements}$$

Two methods of doing this, both w/ same answer

1. Optimization problem

$$\min \sum_i w_i r_i^2$$

$$\text{st } r_i = z_i - h_i(x) \quad \text{where } h(x) = a + bt + e(t)$$

```

1 using JuMP
2 import GAMS
3 using DataFrames
4
5 function solve_wls(weights)
6     model = Model(GAMS.Optimizer)
7     set_optimizer_attribute(model, "solver", "CPLEX")
8     #
9     # SETS
10    years = 1:5
11    #
12    # PARAMETERS
13    measurements = [6197, 6337, 7411, 7940, 8473]
14    #
15    # DECISION VARIABLES
16    @variable(model, R[years]) # residual
17    @variable(model, A) # intercept
18    @variable(model, B) # slope
19    #
20    # OBJECTIVE
21    @objective(model, Min, sum(weights[i] * R[i]^2 for i in years))
22    #
23    # CONSTRAINTS
24    for i in years
25        @constraint(model, R[i] == measurements[i] - (A + B * years[i]))
26    end
27
28    optimize!(model)
29
30    v = all_variables(model)
31    df = DataFrame(
32        variable=name.(v),
33        val=value.(v),
34    )
35    show(df, eltypes=false)
36
37    demand_year_6 = value(A) + value(B) * 6
38    println("\n\nIntercept (A): $(round(value(A), digits=1)), Slope (B): $(round(value(B), digits=1))")
39    println("forecasted peak demand in year 6: $(round(demand_year_6, digits=1)) MW\n\n")
40    return demand_year_6
41 end
42
43 weights = ones(length(years))
44 equal_weights_wls = solve_wls(weights)
45
46 T = 5
47 weight(t) = 0.7^(T - t)
48 weights = weight.(years)
49 weighted_wls = solve_wls(weights)

```

Equal Weights (same answer as problem 1)

Intercept (A): 5425.1, Slope (B): 615.5
forecasted peak demand in year 6: 9118.1 MW

Weighted

Intercept (A): 5419.0, Slope (B): 617.5
forecasted peak demand in year 6: 9124.2 MW

2. Using closed form solution

$$X = (H^T W H)^{-1} \cdot H^T W z$$

where W = diagonal matrix with w_i^2 on diagonal

$$H = \frac{\partial h}{\partial x} = \begin{bmatrix} \frac{\partial(a+b \cdot 1)}{\partial a} & \frac{\partial(a+b \cdot 1)}{\partial b} \\ \frac{\partial(a+b \cdot 2)}{\partial a} & \frac{\partial(a+b \cdot 2)}{\partial b} \\ \vdots & \vdots \\ \frac{\partial(a+b \cdot 5)}{\partial a} & \frac{\partial(a+b \cdot 5)}{\partial b} \end{bmatrix}$$

$h = a + b \cdot t + e(t)$

$x = \begin{bmatrix} a \\ b \end{bmatrix}$

$z = \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \\ 1 & 5 \end{bmatrix}$

Note that $\frac{\partial e(t)}{\partial a} = \frac{\partial e(t)}{\partial b} = 0$

```

1 using LinearAlgebra
2
3 years = 1:5
4 measurements = [6197, 6337, 7411, 7940, 8473]
5
6 ## CLOSED FORM SOLUTION
7 # equal weights scenario
8 H = hcat(ones(5), years)
9 z = measurements
10 W = diagm(ones(5)) # weights
11
12 X = (H' * W * H)^-1 * H' * W * z
13 a = X[1]
14 b = X[2]
15 println("\n\nIntercept (A): $(round(a, digits=1)), Slope (B): $(round(b, digits=1))")
16 println("forecasted peak demand in year 6: $(round(a + b*6, digits=1)) MW\n\n")
17
18 # weighted scenario
19 T = 5
20 weight(t) = 0.7^(T - t)
21 weights = weight.(years)
22 W = diagm(weights) # weights
23
24 X = (H' * W * H)^-1 * H' * W * z
25 a = X[1]
26 b = X[2]
27 println("\n\nIntercept (A): $(round(a, digits=1)), Slope (B): $(round(b, digits=1))")
28 println("forecasted peak demand in year 6: $(round(a + b*6, digits=1)) MW")

```

Equal
Weights

Intercept (A): 5425.1, Slope (B): 615.5
forecasted peak demand in year 6: 9118.1 MW

Weighted

Intercept (A): 5419.0, Slope (B): 617.5
forecasted peak demand in year 6: 9124.2 MW

3. For problem 1 assume a Markov model of the form $d(t) = a \cdot d(t-1) + e(t)$. Find coefficient a using the correlation method. Determine the demand forecast for years 6 and 7.

$$d(t) = a \cdot d(t-1) + e(t)$$

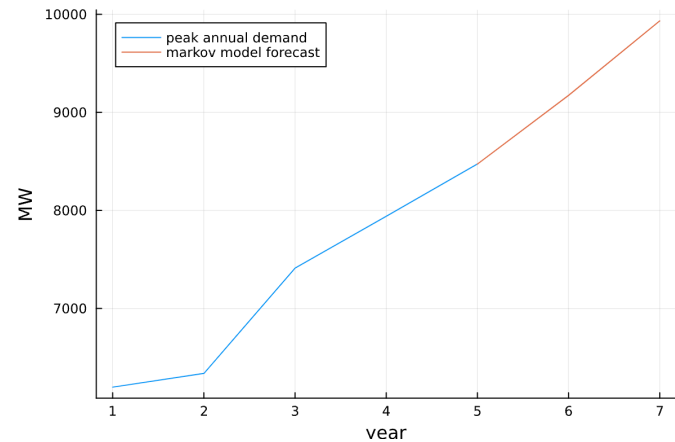
multiply both sides by $d(t)$ and take expectation

$$E[d(t) \cdot d(t)] = a E[d(t) \cdot d(t-1)] + E[d(t) \cdot e(t)]$$

0

$$a = \frac{E[d(t) \cdot d(t)]}{E[d(t) \cdot d(t-1)]}$$

$a = 1.083$
 forecasted demand in year 6 = 9173.8 MW
 forecasted demand in year 7 = 9932.5 MW



```

1 using Statistics
2 using Plots
3
4 years = 1:5
5 d = [6197.0, 6337.0, 7411.0, 7940.0, 8473.0]
6
7 numerator = mean(d[2:end] .* d[2:end]) # not sure if this should be 1:end or 2:end
8 denominator = mean(d[2:end] .* d[1:end-1])
9
10 a = numerator / denominator
11 println("a = $(round(a, digits=3))")
12
13 d_pred = [d[end]]
14 for i in 1:2
15     d_t = a * d_pred[end]
16     push!(d_pred, d_t)
17 end
18
19 d_pred_first = []
20 for i in 2:5
21     push!(d_pred_first, a * d[i-1])
22 end
23
24 println("forecasted demand in year 6 = $(round(d_pred[2], digits=1)) MW")
25 println("forecasted demand in year 7 = $(round(d_pred[3], digits=1)) MW")
26
27 plt = plot(years, d,
28     label="peak annual demand",
29     ylabel="MW",
30     xlabel="year",
31 )
32 plot!(5:7, d_pred, label="markov model forecast")
33 display(plt)

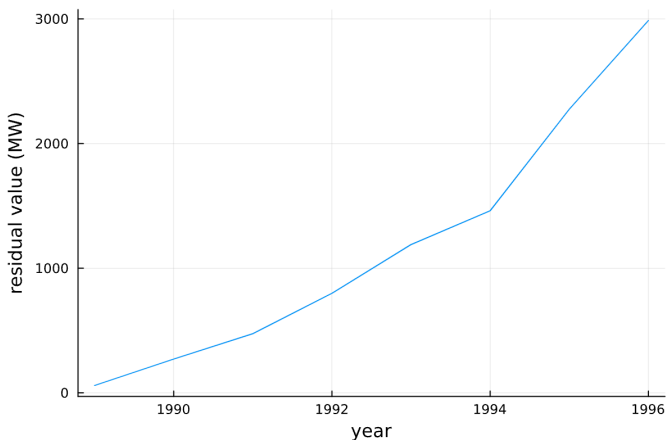
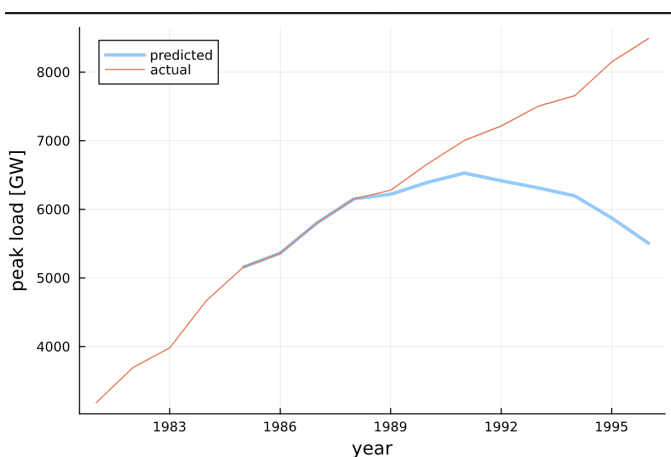
```

4. The peak load data for a utility company is given in the table below. Assume that only the load data for years 1981–1988 is available. Using this data, derive a time-series linear model for the peak demand based on its four past values, i.e. demand at year t is a linear function of demands of the previous four years. Use the model and its estimated load values to predict the demand for years 1989–1996. Compare with the actual values provided in the table below.

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1991	7,004
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1995	8,149
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available

$$d(t) = \sum_{k=1}^4 a_k d(t-k) + e(t)$$



	Coef.
(Intercept)	0.0
d_t_1	1.29289
d_t_2	-0.362
d_t_3	0.853222
d_t_4	-0.815682

Model looks like

$$d(t) = 1.29 \cdot d(t-1) - 0.36 \cdot d(t-2) + 0.85 \cdot d(t-3) - 0.82 \cdot d(t-4)$$

Clearly, the model is not a good fit. The residual plot shows a clear trend of increasing over time.

years	actual MW	predicted MW	residual MW
1981	3179.0	-----	-----
1982	3694.0	-----	-----
1983	3981.0	-----	-----
1984	4672.0	-----	-----
1985	5158.0	5158.0	6.91216e-11
1986	5361.0	5361.0	5.00222e-11
1987	5803.0	5803.0	2.54659e-11
1988	6152.0	6152.0	6.54836e-11
1989	6279.0	6220.0	59.0036
1990	6664.0	6393.11	270.889
1991	7004.0	6529.56	474.443
1992	7215.0	6416.64	798.359
1993	7503.0	6313.5	1189.5
1994	7657.0	6196.24	1460.76
1995	8149.0	5874.34	2274.66
1996	8491.0	5504.7	2986.3

CODE on following page

```

1 using DataFrames, GLM, StatsModels
2 using Plots
3 using PrettyTables
4
5 years = 1981:1996
6 demands = Float64.([3179, 3694, 3981, 4672, 5158, 5361, 5803, 6152, 6279, 6664, 7004, 7215,
7503, 7657, 8149, 8491])
7
8 train_years = 1981:1988
9 train_d = demands[1:length(train_years)]
10
11 # have to start at 5 so you have t - 4 data available
12 df = DataFrame(
13     y=train_years[5:end],
14     d_t=train_d[5:end],
15     d_t_1=train_d[4:end-1],
16     d_t_2=train_d[3:end-2],
17     d_t_3=train_d[2:end-3],
18     d_t_4=train_d[1:end-4],
19 )
20
21 model = lm(@formula(d_t ~ d_t_1 + d_t_2 + d_t_3 + d_t_4), df)
22
23 predict(model, df)
24
25 pred_demands = train_d[1:4]
26 for (i, year) in enumerate(1985:1996)
27     intercept, a, b, c, d = coef(model)
28     d_next = (
29         intercept
30         + a * pred_demands[end]
31         + b * pred_demands[end-1]
32         + c * pred_demands[end-2]
33         + d * pred_demands[end-3]
34     )
35     push!(pred_demands, d_next)
36 end
37
38
39 println("Model is")
40 println(model)
41
42 plt = plot(years, pred_demands, label="predicted")
43 plot!(years, demands, label="actual", ylabel="peak load [GW]", xlabel="year")
44 display(plt)
45
46 df_answer = DataFrame(
47     years=years,
48     actual=demands,
49     predicted=[missing, missing, missing, missing, pred_demands[5:end]...],
50     residuals=[missing, missing, missing, missing, (demands - pred_demands)[5:end]...]
51 )
52 plot(1989:1996, df_answer[9:16, "residuals"], xlabel="year", ylabel="residual value (MW)",
53     legend=:none)
54 df_final = coalesce(df_answer, "—")
55
56 header = (["years", "actual", "predicted", "residual"], ["", "MW", "MW", "MW"])
57 pretty_table(df_final, header=header, header_crayon=crayon"yellow bold")

```