POWER GENERATING STATIONS
conventional steam power plants

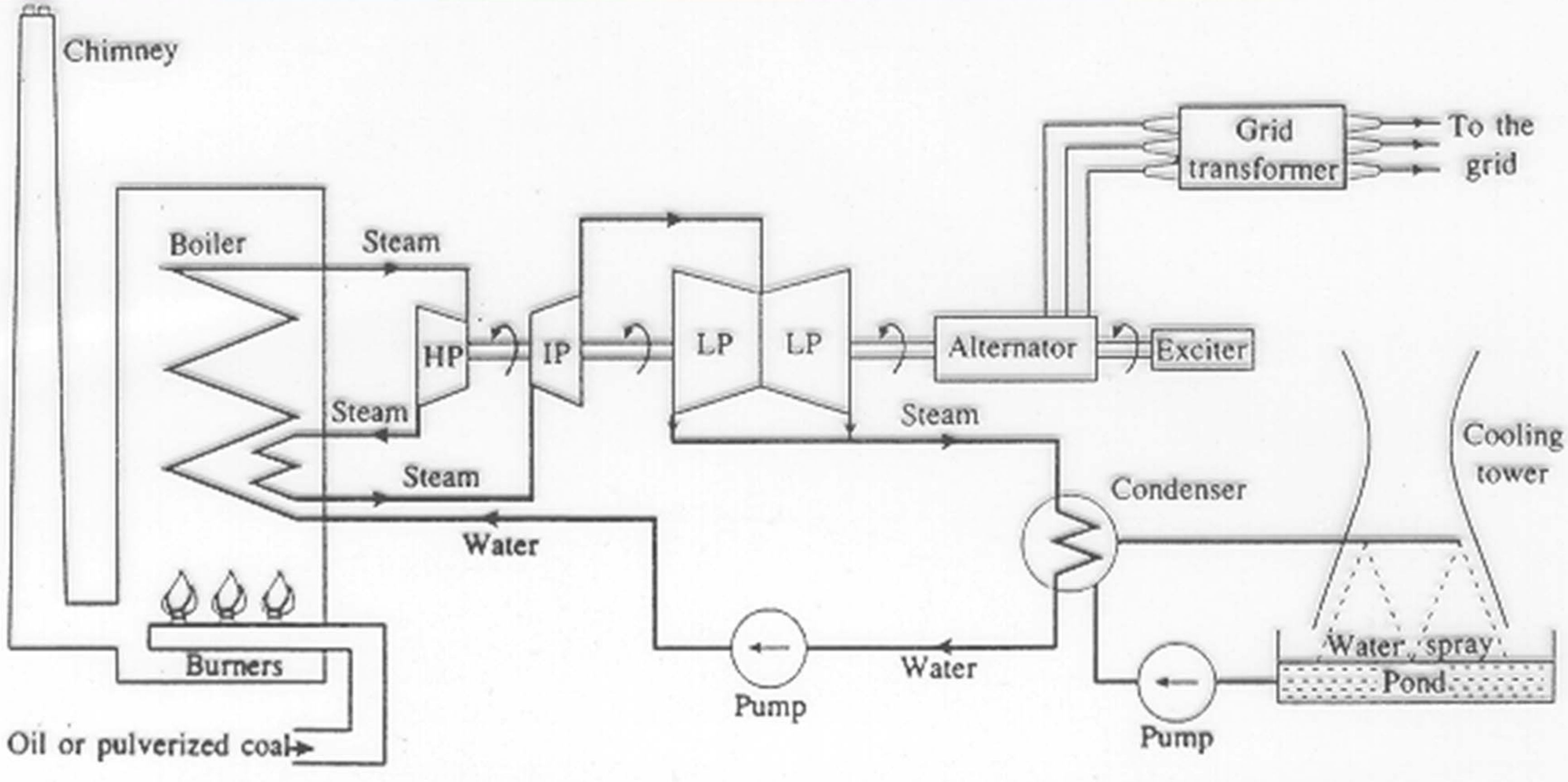


Figure 7.1 *Schematic diagram of a coal- or oil-burning power station. HP, IP and LP are the high-pressure, intermediate-pressure and low-pressure turbines respectively*

POWER GENERATING STATIONS

conventional steam power plants

Steam produced by coal, oil or peat

Efficiency at maximum about 40%

Base-load or intermediate generation

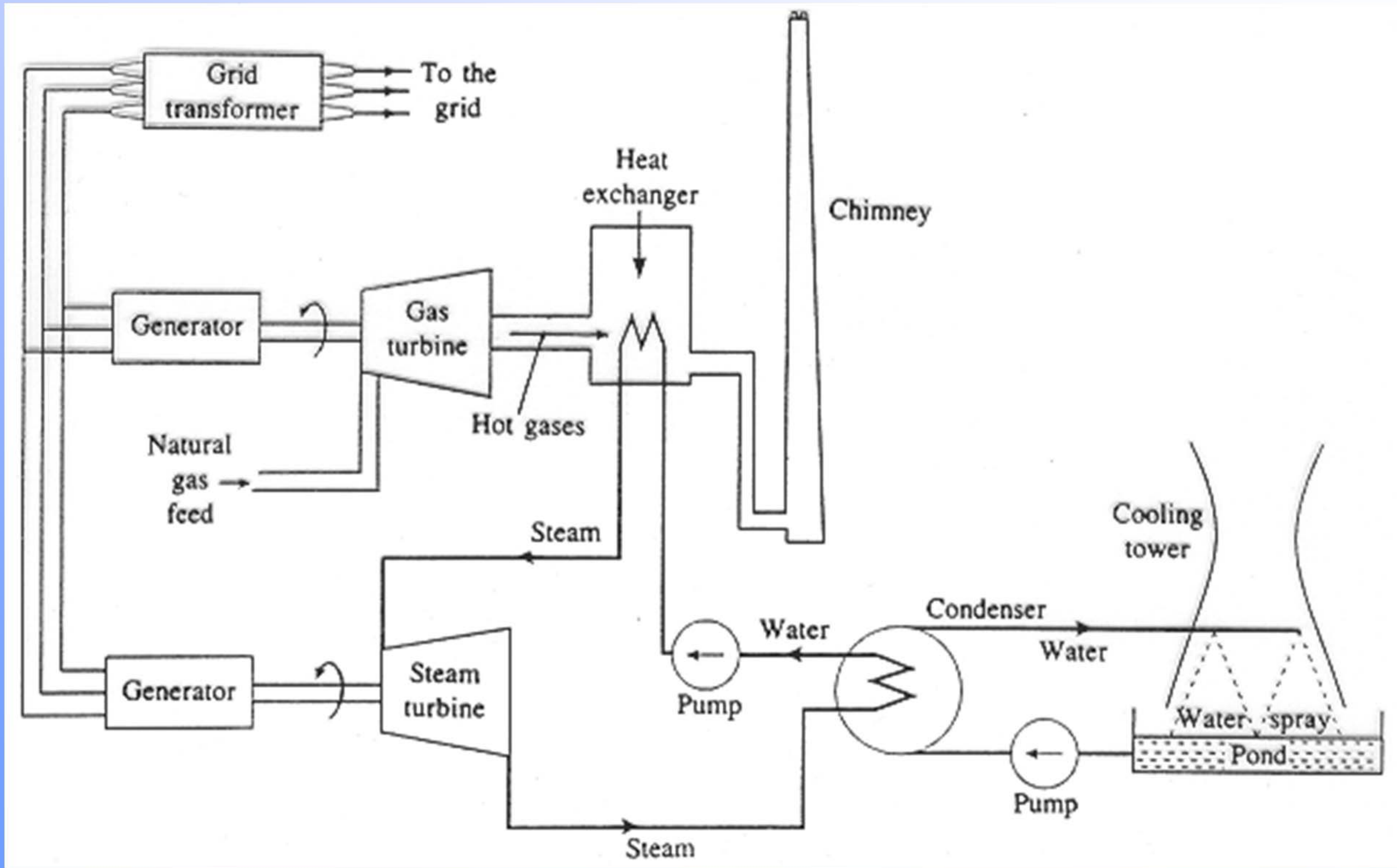
High environmental impact due to CO_2, SO_2 and NO_x

Efficiency increased if waste heat energy is used
for district heating

$\Rightarrow$condenser replaced by heat exchanger

$\Rightarrow$"back-pressure power plant "

POWER GENERATING STATIONS
combined-cycle power stations



POWER GENERATING STATIONS
combined-cycle power stations

One generator driven by a gas turbine, one with steam

The exhaust heat of gas turbine is utilised in steam production

The emission of SO_2 and NOx better controlled than in conventional plants (gasification)

In back-pressure connection, thermal efficiency is very high; yield of electricity and heat about 50/50

POWER GENERATING STATIONS
Nuclear power plants

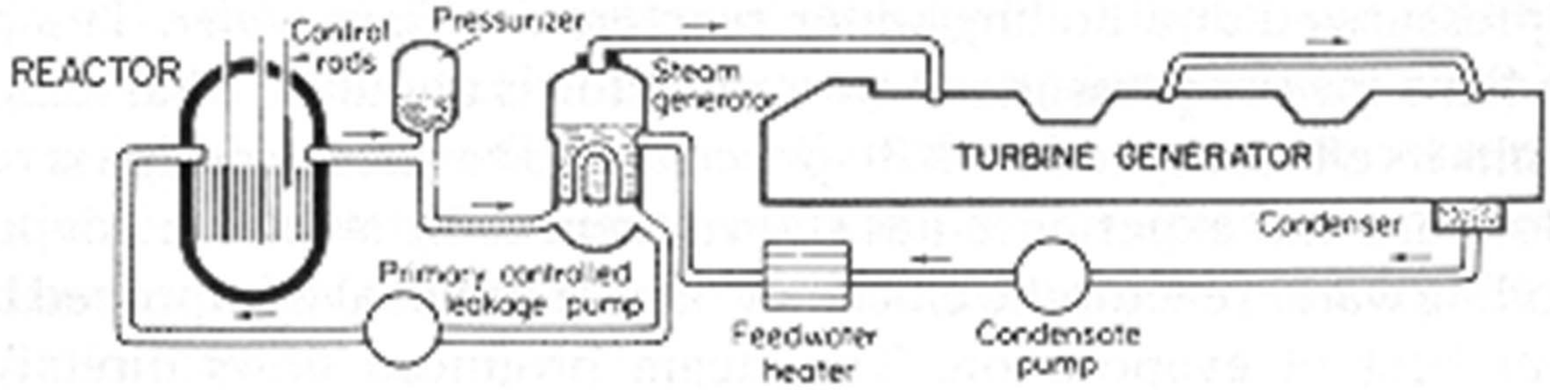


Figure 1.17 Schematic diagram of a pressurized water reactor. (*Permission of Edison Electric Institute.*)

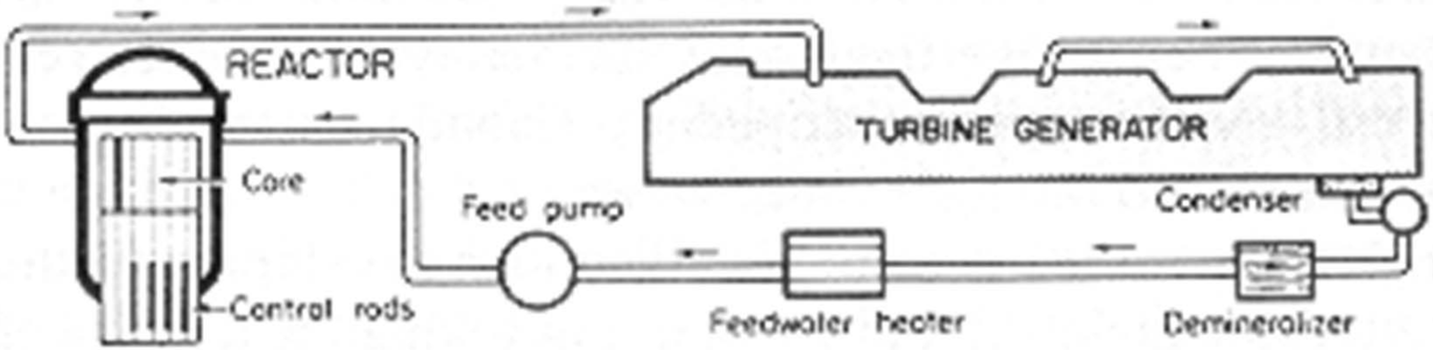


Figure 1.18 Schematic diagram of a boiling water reactor. (*Permission of Edison Electric Institute.*)

POWER GENERATING STATIONS
Nuclear power plants

Conventional steam plants beyond the heat producing reactor

High investments – low fuel costs => base load production

No emissions of CO_2 , SO_2, or NO_x

Open questions: final treatment of used fuel

Present plants based on fission of uranium-235 (0,7% of all U)

Fast-breeder reactors: uranium-238 converted to plutonium

Fusion energy: D+T= He+n or D+D=T+H or D+D=He+n

POWER GENERATING STATIONS
Hydro power plants

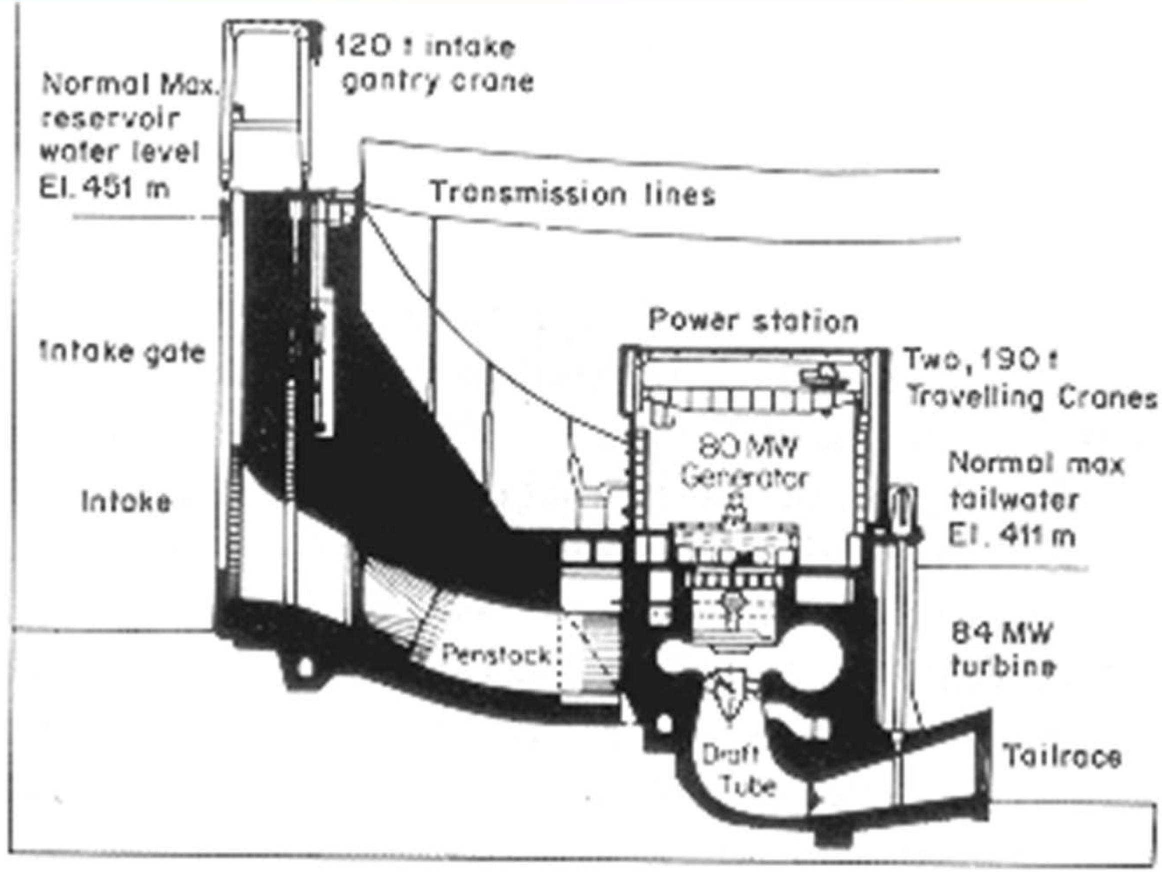


Figure 1.12 Hydroelectric scheme—Kainji, Nigeria. Section through the intake dam and power house. The scheme comprises an initial four 80 MW Kaplan turbine sets with the later installation of eight more sets. Running speed 115.4 rev/min. This is a large-flow scheme with penstocks 9 m in diameter. (*Permission of Engineering.*)

POWER GENERATING STATIONS
Hydro power plants

High investments, but no fuel costs

Variation of water flows: reservoir often needed

Limitations of operation:
$\Rightarrow$flood control
$\Rightarrow$limited variation of water level

Very good properties for generated power control
=> used for production / demand balance control

No emissions of CO_2 , SO_2, or NO_x

Properties of different power plant types

Hydro power

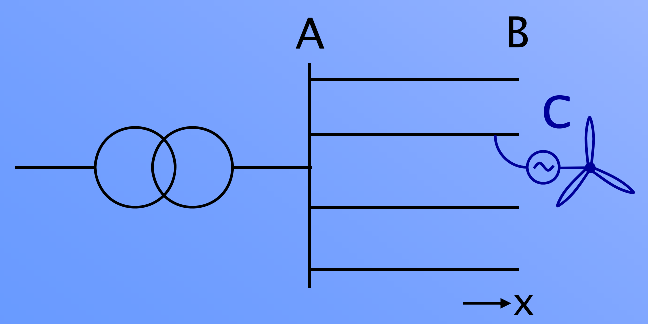
- high investments
- variable inflow
  - reservoirs needed
- good power control properties
- limitations of utilisation
  - flood control
  - water level variation limits
- as reservoir natural or artificial lakes

Solar power

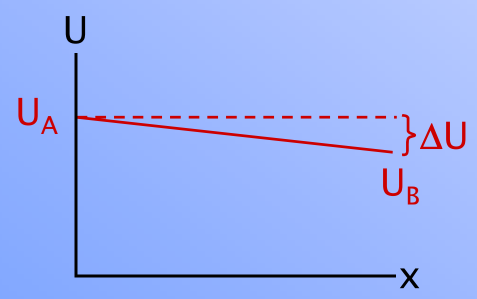
- small efficiency of the cell n. 15 %
- amount of light a problem in Finland

Wind power

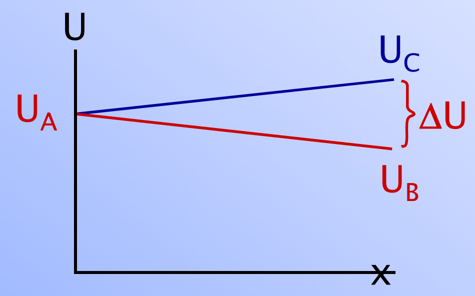
- economic size ~ 5–10 MW
- large wind parks 100 – 1000 MW
- network connection sometimes troublesome



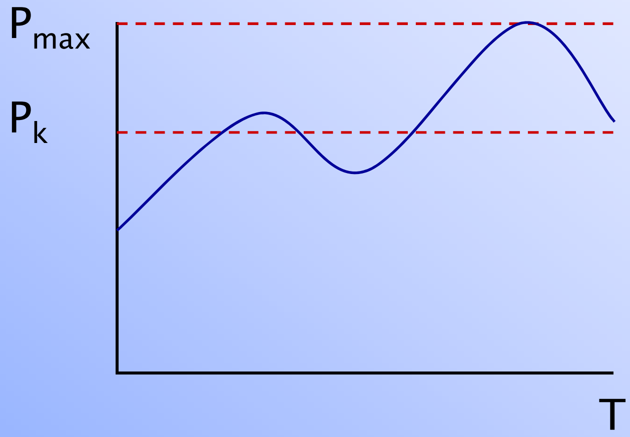
Network voltage normally

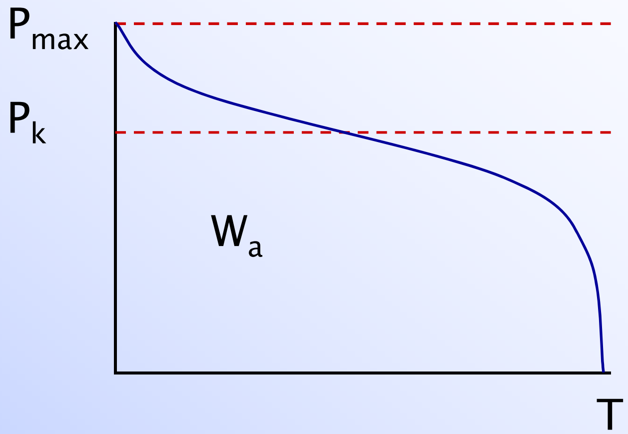


And if wind power in C



Load variation and load duration curve





Load duration curve is obtained by arranging the hourly demands in descending order

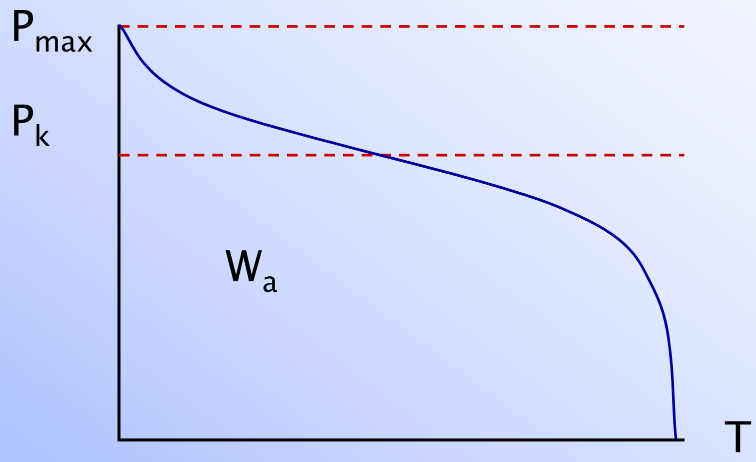
Load factor $$\varepsilon = \frac{P_k}{P_{max}}$$

Load duration time $$t_k = \frac{W_a}{P_{max}} = \frac{P_k T}{P_{max}} = \varepsilon T$$

- W_a = annual energy
- P_k = mean power
- P_{max} = max power

Load factor is per unit load duration time

LOAD DURATION CURVE



P_{max} = max power
P_k = mean power
W_a = annual energy

Load duration time $t_k = \frac{W_a}{P_{max}}$

Sum of loads connected $P_l = \sum_{i=1}^{n} P_i$

Load factor $\varepsilon = \frac{P_k}{P_{max}}$

Diversity factor $k = \frac{P_l}{P_{max}}$

Coincidence factor $c = \frac{P_{max}}{P_l}$

Coincidence factor = 1/Diversity factor

Assessing the maximum load

$P_{max} = f(W_a)$?

Velander equation :

$$\frac{P_{max}}{MW} = k_1 \frac{W_a}{GWh} + k_2 \sqrt{\frac{W_a}{GWh}}$$

Coefficients k_1 and k_2 are experimental

	k_1	k_2
Industry	0,28	0,79
Space heating	0,30	0,79
Housing	0,33	1,52

Assessing the maximum load

How Velander equation comes :

The maximum of a sum of loads:

$$P_{max} = \sum_{i}^{m} P_{ki} + \alpha \sqrt{\sum_{i}^{m} P_{\sigma i}^{2}}$$

α = factor depending on distribution
P_{ki} = average power of load i
$P_{\sigma i}$ = statistical deviation of load i

$$\Longleftrightarrow \quad (P_{maxi} - P_{ki} = \alpha P_{\sigma i})$$

$$P_{max} = \sum_{i}^{m} P_{ki} + \sqrt{\sum_{i}^{m} (P_{maxi} - P_{ki})^{2}}$$

Assume average and maximum loads equal compared each other

$$\Rightarrow P_{max} = m P_{ki} + (P_{maxi} - P_{ki}) \sqrt{m}$$

Total energy $W_a = mW_{ai}$

$\Rightarrow m = W_a / W_{ai}$ $\quad \Rightarrow$ Substitute above

$$P_{max} = \frac{W_a}{W_{ai}} \cdot P_{ki} + \sqrt{\frac{W_a}{W_{ai}}} \cdot (P_{maxi} - P_{ki})$$

$$P_{max} = \underbrace{\frac{P_{ki}}{W_{ai}}}_{k_1} \cdot W_a + \underbrace{\frac{P_{maxi} - P_{ki}}{\sqrt{W_{ai}}}}_{k_2} \cdot \sqrt{W_a}$$

Note: W_a = total annual energy & W_{ai} = single load annual energy

Modelling and forecasting load variation

Type users load curves

$$P_{ri} = \frac{E_r}{8736} \frac{Q_{ri}}{100} \frac{q_{ri}}{100}$$

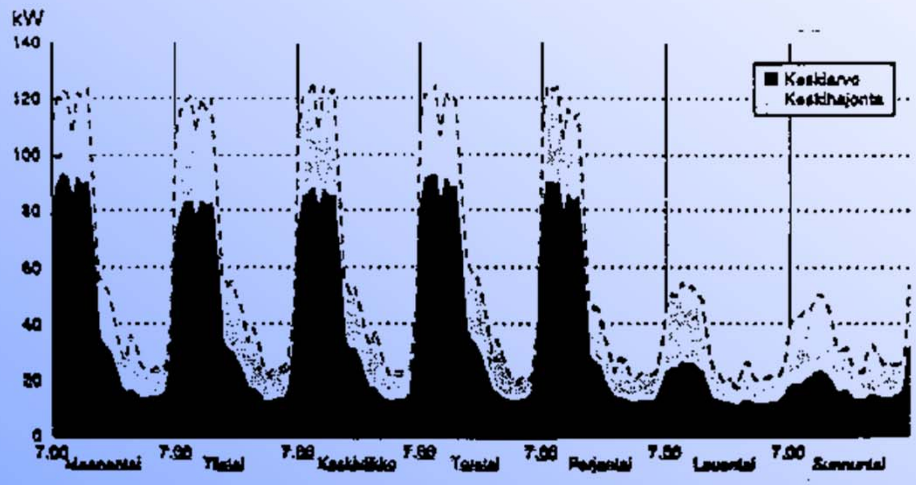
- P_{ri} mean power of customer type r at hour i
- E_r annual energy
- Q_{ri} external index
  (seasonal variation: 26   2 week periods)
- q_{ri} internal index
  (24 hourly values, workday, eves, sundays)
  – special days

In addition the statistical variations in same form

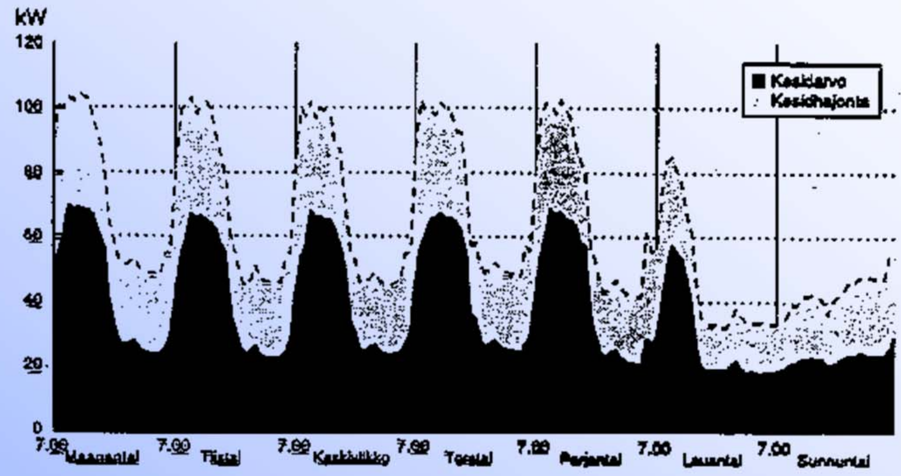
Modelling and forecasting load variation

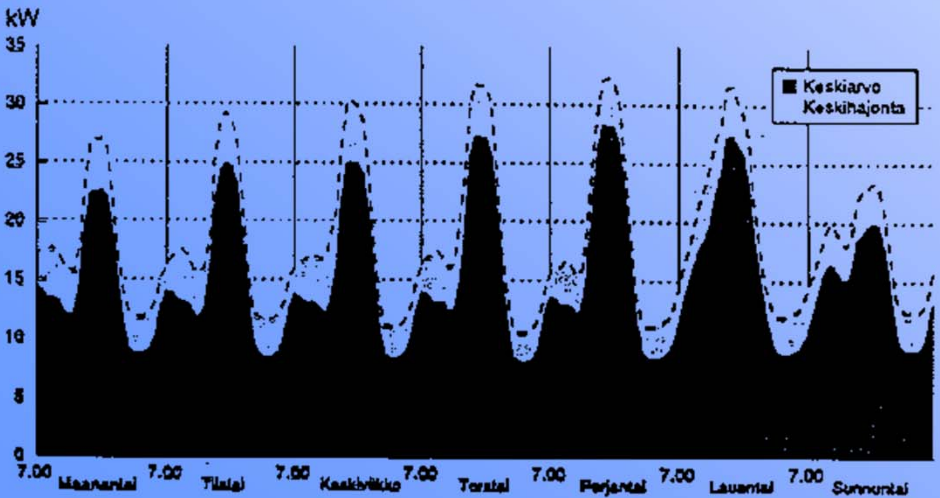
Examples of load variation among different types of customers
Mean demand and variance (dotted)

1- phase metal industry



Retail sales





Apartment house

Factors affecting the load variation

1) Temperature
2) Wind velocity
3) Light density

A model for temperature correction

$$q_{tod}(t) = q_0(t) + \beta \Delta T(t)$$

where

$q_{tod}(t)$ = measured power demand

$q_0(t)$ = demand in normal ambient temperature t

β = temperature dependence coefficient (2–4% if heating)

$\Delta T(t)$ = difference between actual and normal temperature

Errors of load models

1) Errors of input data
   - annual energy
   - LV-network topology

2) Selection of type model
   - untypical loads
   - change of load behavior
   - errors on load classification

3) Errors related to the temperature
   - incorrect data of temperatures
   - incorrect temperature correction

Regression analysis in load forecasting

Input data
- previous load behavior
- weather data

$$y = y_B + y_W + y_D + a_1 T + a_2 W + a_3 L + a_4 P$$

Base load (y_B, y_W, y_D), average, week, day
temperature T
wind velocity W
light intensity L
degree of precipitation P

Regression analysis: Least square estimate

$$\sum_{1}^{n} \varepsilon^2 = \sum (y - y_B - y_W - y_D - a_1 T - a_2 W - a_3 L - a_4 P)^2$$

Define the coefficients $a_1 \ldots a_4$ and y_D
such, that $\Sigma\varepsilon^2$ is minimized

=> coefficients & weather forecast
=> load forecast

Accuracy for 24 hour forecast even 1,4 %
(bulk power system level)

Time series - analysis

Transforming a non-stationary time series into a stationary by differentiation

Data in sample form

$$z_t = f(x_t)$$

Differentiating

$$w_t = (1-B)^d (1-B^s)^D z_t$$

$$(1-B)z_t = z_t - z_{t-1}$$

Usually is written

$$\nabla^d \triangleq (1-B)^d \quad \text{ja} \quad \nabla_s^D \triangleq (1\text{-}B^s)^D$$

$$w_t = \nabla^d \nabla_s^D z_t$$

Time series model consist of two components:

1) Auto-regressive (AR)

$$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$$
$$\Phi_P(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \ldots \Phi_P B^{Ps}$$

2) Moving average (MA)

$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$$
$$\Theta_Q(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} - \ldots \Theta_Q B^{Qs}$$

Model construction:

$$\phi_p(B)\Phi_p(B^s)w_t = \theta_q(B)\Theta_Q(B^s)a_t$$

w_t is a stationary time series

a_t is white noise

Defining the parameters p, P, q and Q

They depend on the cycle of time series

- Auto-correlation
- Fourier-transform

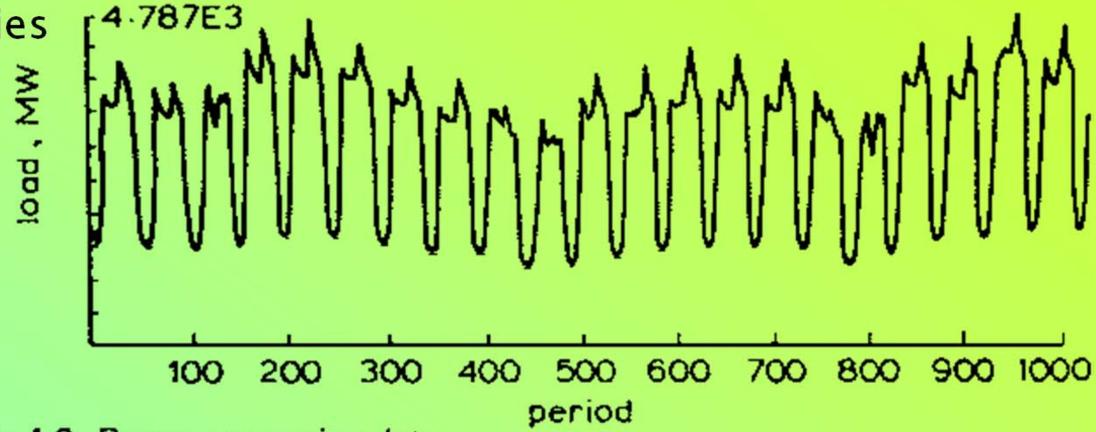


Fig. 4.9 Raw consumption data

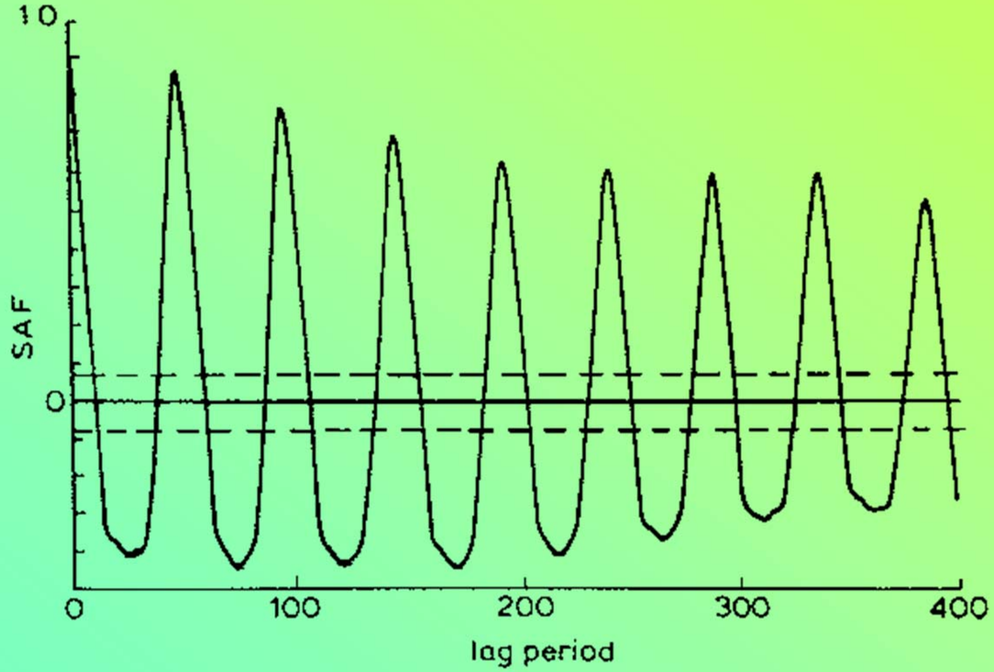


Fig. 4.10 Sample autocorrelation of raw data

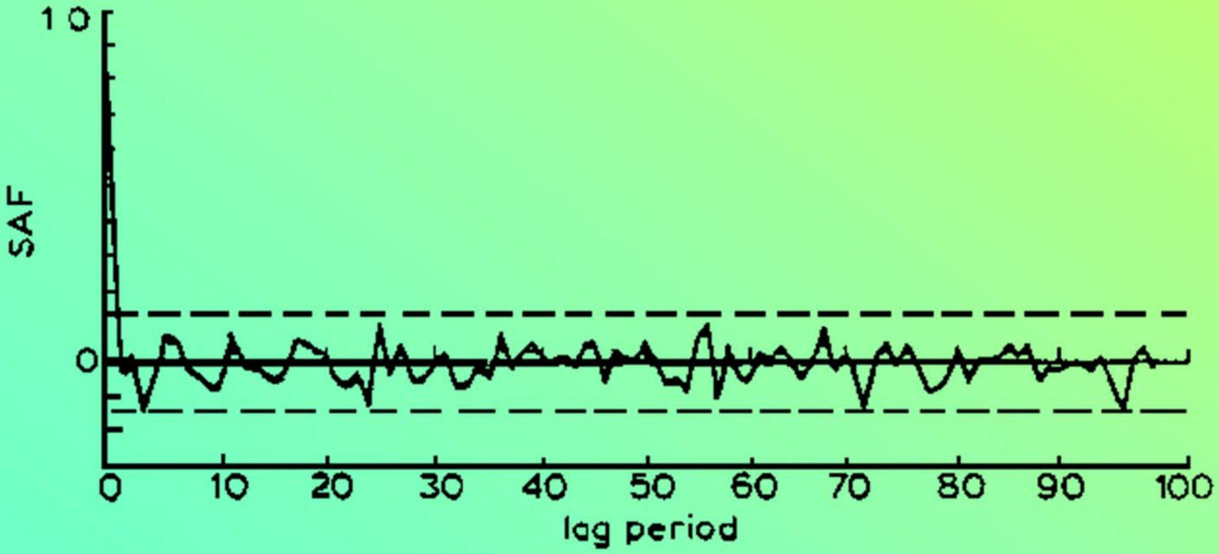
Defining the coefficients of polynomials

- by minimizing the error square sum

$$s = \sum_t a_t^2(\phi, \Phi, \theta, \Theta)$$

- Methods
  - mathematical iteration methods
  - least squares estimation (regression)

Evaluation of the result using auto-regression of the residuals



Sample autocorrelation of residuals

An example model

$$(1 - 0{,}3641B - 0{,}09552B^2)w_t = (1 - 0{,}8B^{48})(1 + 0{,}241B^{336})\, a_t$$

Forecasting by the model:

- we know: $w_t(0)$ – $w_t(n)$, $a_t(0)$ – $a_t(n)$
- we set: $a_t(> n) = 0$

=> we solve: $w_t(> n)$

=> re-transformation into non-stationary series z_t