Import packages

In [1]:
```
using DataFrames, Plots, Statistics, JSON, Distributed
plotlyjs();
```

The WebIO Jupyter extension was not detected. See the WebIO Jupyter integration documentation for more information.

Prepare parallell processing - import code on all cores

The problem is simulated on 31 2.20 GHz processors running in parallel. TODO: Test on faster processors.

In [2]:
```
const numcores = 31

if nprocs() < numcores
    addprocs(numcores - nprocs())
end

@show nprocs();
```

```
nprocs() = 31
```

In [43]:
```
@everywhere include(joinpath(dirname(pwd()),"jgrc/TuLiPa/src/TuLiPa.jl"));
```

In [44]:
```
@everywhere include(joinpath(dirname(pwd()),"jgrc/JulES/src/JulES.jl"));
```

Starting point and scenario settings

- Start model year 2025 and weather scenario 1981
- Series simulation 30 years with moving horizons and two day time steps.
- 7 weather years considered for uncertainty (always the next 7 years, TODO: replace with scenario generation from all 30 scenarios)
- Scenarios are phased in after two days
  - First two days have perfect information from starting point scenario
  - Next 5 weeks combines starting point scenario and scenario X. Smooth transition.
  - After 5 weeks the starting point scenario is fully phased out.

In [45]:
```
datayear = 2025
scenarioyearstart = 1981
scenarioyearstop = 2011
numscen = 7

tnormal = FixedDataTwoTime(getisoyearstart(datayear),getisoyearstart(scenarioyearstart))

phaseinoffsetdays = 2
phaseinoffset = Millisecond(Day(phaseinoffsetdays)) # phase in straight away from second s
phaseindelta = Millisecond(Week(5)) # Phase in the second stage scenario over 5 weeks
phaseinsteps = 5 # Phase in second stage scenario in 5 steps
tphasein = PhaseinTwoTime(getisoyearstart(datayear),getisoyearstart(scenarioyearstart), ge
```

Price prognosis models uses the Thema dataset

This is a simplified version of the dataset NVE uses for its long-term power market analyses (for example https://www.nve.no/energi/analyser-og-statistikk/langsiktig-kraftmarkedsanalyse/). The dataset consist of:

- Detailed thermal units, aggregated hydro (Res, RoR, PHS), inelastic wind and solar, demands (inelastic with rationing price), storages (hydro and battery), transmission (ATC) and price areas (endogenous and exogenous).
- Levels in 2021, 2025, 2030, 2040 and 2050 (e.g. commodity price levels, installed production/transmission/storage capacities etc.)
- Profiles (e.g. availability profiles for transmission or production units, commodity price profiles, weather scenario profiles 1981-2010 for demand, solar, wind and inflow etc.)

We cannot publish the full dataset, but many of the profiles for wind, solar, hydro and demand can be downloaded from https://www.nve.no/energi/analyser-og-statistikk/vaerdatasett-for-kraftsystemmodellene/.

NB!

- In this demo we use the model year 2025. This scenario was made a couple of years ago and results should be considered outdated. A lot has happened in the power market since then. In addition the dataset is simplified.

In [46]:
```
sti_themadata = "data_fra_thema"

themastructure = json_to_elements(sti_themadata, "dataset_thema.json")
themaseries = json_to_elements(sti_themadata, "tidsserier_thema.json")

elements = vcat(themaseries,themastructure)
addscenariotimeperiod!(elements, scenarioyearstart, scenarioyearstop);
```

Initialize and run price prognosis models

- Three levels of details: Long, medium and short term problems (run sequentially)
- Seven scenarios (run in parallell)
- Inputs:
  - Power market representation / Thema-data. (And how to aggregate it)
  - Problem length and time resolution
    - Long: 5 years long horizon with 6-weekly resolution for hydro, divided into 4 dynamic load blocks for power
    - Med: 54 week long horizon with weekly resolution for hydro, divided into 4 dynamic load blocks for power
    - Short: Week long horizon with daily resolution for hydro, and two-hourly for power
- Outputs:
  - Long, medium and short term prices for use in stochastic subsystem models.
  - Storage values (water values) from medium for use as end condition in stochastic subsystem models.
  - Thermal end states from short for use as end condition in market clearing model

In [47]:
```
# Set horizons for price prognosis models
# Long
longhorizonend = getisoyearstart(scenarioyearstart + 5)
longhydroperiodduration = Millisecond(Week(6))
longpowerparts = 6

longrhsdata = StaticRHSAHData("Power", datayear, scenarioyearstart, scenarioyearstop)
```

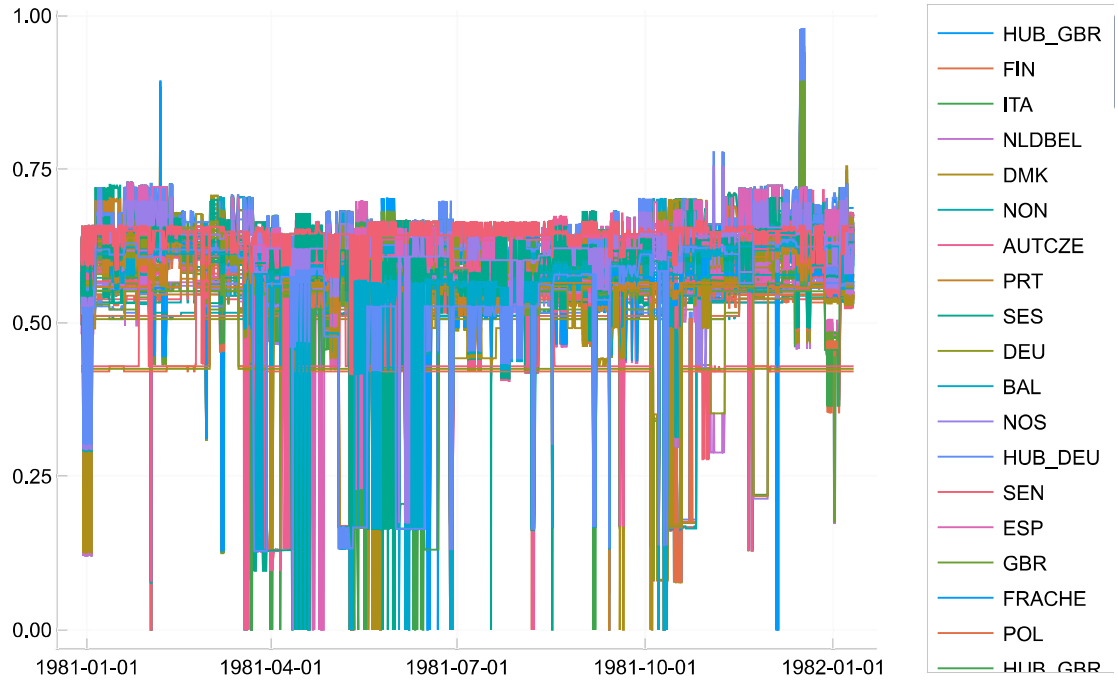
```
longmethod = KMeansAHMethod()
longclusters = 4
longunitduration = Millisecond(Hour(6))

# Medium
medweeklength = 54
medhorizonend = getisoyearstart(scenarioyearstart) + Week(medweeklength)
medhydroperiodduration = Millisecond(Day(7)); @assert medweeklength % Int(longhydroperiodd
medpowerparts = 7

medrhsdata = DynamicRHSAHData("Power")
medmethod = KMeansAHMethod()
medclusters = 4
medunitduration = Millisecond(Hour(4))

# Short
shortweeklength = 1
shorthorizonend = getisoyearstart(scenarioyearstart) + Week(shortweeklength)
shorthydroperiodduration = Millisecond(Day(1)); @assert medweeklength % shortweeklength ==
shortpowerparts = 12

# Preallocate storage for problems and results on different cores. Use package Distributed
# Problems are built, updated, solved, and stored on a specific core. Moving a problem bet
longprobs = distribute([HiGHS_Prob() for i in 1:numscen])
medprobs = distribute([HiGHS_Prob() for i in 1:numscen], longprobs)
shortprobs = distribute([HiGHS_Prob() for i in 1:numscen], longprobs)

# Results are moved between cores. These are much smaller than longprobs/medprobs/shortprob
medprices = distribute([Dict() for i in 1:numscen], longprobs)
shortprices = distribute([Dict() for i in 1:numscen], longprobs)
medendvaluesobjs = distribute([EndValues() for i in 1:numscen], longprobs)
nonstoragestates = distribute([Dict{StateVariableInfo, Float64}() for i in 1:numscen], lon

# Organise inputs and outputs
probs = (longprobs, medprobs, shortprobs)
longinput = (longhorizonend, longhydroperiodduration, longrhsdata, longmethod, longcluster
medinput = (medhorizonend, medhydroperiodduration, medrhsdata, medmethod, medclusters, med
shortinput = (shorthorizonend, shorthydroperiodduration, shortpowerparts, "short")
allinput = (numcores, elements, scenarioyearstart, tnormal, tphasein, phaseinoffsetdays)
output = (medprices, shortprices, medendvaluesobjs, nonstoragestates)

# Initialize price prognosis models and run for first time step. Run scenarios in parallel
@time pl_prognosis_init!(probs, allinput, longinput, medinput, shortinput, output)
```

```
 23.807784 seconds (3.23 M allocations: 124.873 MiB, 0.34% compilation time)
```

Out[47]:
```
Task (done) @0x00000000bc672100
```

Plot medium term prices for the 7 scenarios

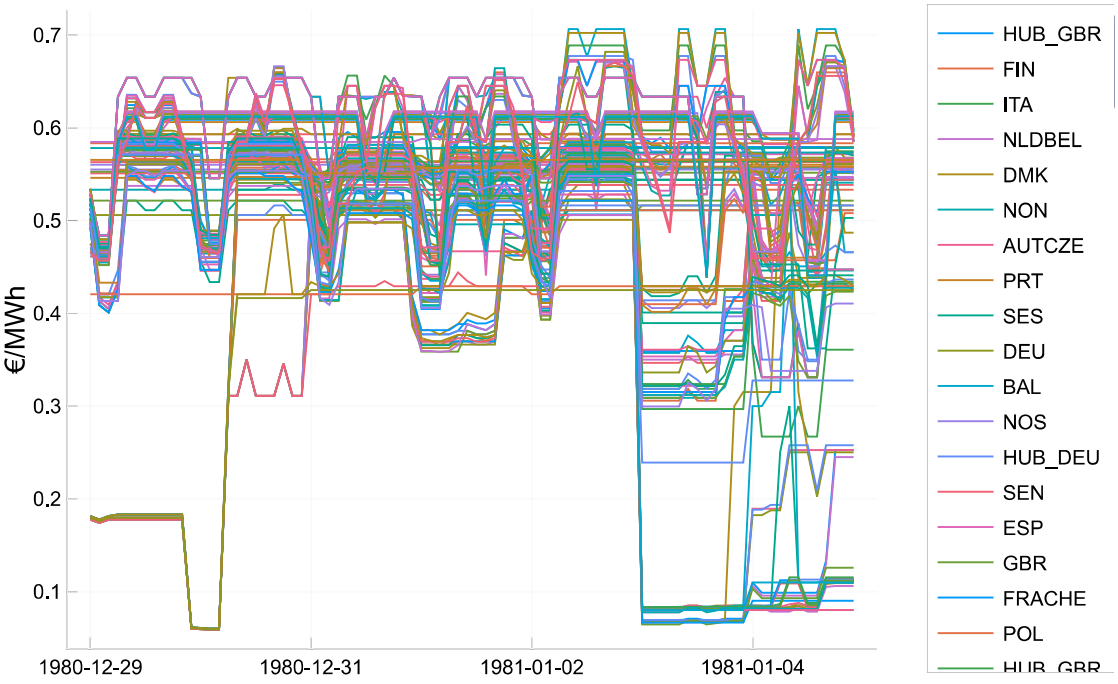
In [48]:
```
scenario = 1
index = collect(medprices[scenario]["steprange"])
prices = medprices[scenario]["matrix"]
labels = [name for name in medprices[scenario]["names"]]
p = plot(index,prices,label=reshape(labels, 1, length(labels)),legend=:outertopright)

for scenario in 2:numscen
    prices = medprices[scenario]["matrix"]
    labels = [name for name in medprices[scenario]["names"]]
    plot!(p,index,prices,label=reshape(labels, 1, length(labels)),legend=:outertopright)
end
display(p)
```



Plot short term prices for the 7 scenarios

In [49]:

```
scenario = 1
index = collect(shortprices[scenario]["steprange"])
prices = shortprices[scenario]["matrix"]
labels = [name for name in shortprices[scenario]["names"]]
p = plot(index,prices,label=reshape(labels, 1, length(labels)), ylabel="€/MWh",legend=:out

for scenario in 2:numscen
    prices = shortprices[scenario]["matrix"]
    labels = [name for name in shortprices[scenario]["names"]]
    plot!(p, index,prices ,label=reshape(labels, 1, length(labels)),legend=:outertopright)
end
display(p)
```



Stochastic subsystem models and market clearing model uses more detailed data

Thema dataset (explained above) combined with detailed hydropower for Norway and Sweden. The full detailed dataset contains for Nortwestern Europe:

- 32 price areas (9 exogen)
- 73 transmission lines (19 with ramping)
- 162 demands
- 88 batteries (normal, and representing demand response and V2G)
- 294 thermal plants (228 with start up costs)
- 100 wind and solar plants (aggregated)
- 1482 hydropower modules
  - 965 with production
  - 43 with pumps (includes PHS)
  - 998 with reservoirs
  - 788 restrictions (environmental, reservoir curves and ramping)
  - 90 PQ-curves (mostly Sweden)

NVEs dataset for the hydropower system in 2022 is open, but we have not published datasets for 2025/2030/2040/2050 since it would reveal investment plans. The dataset exist in several formats:

- Aggregated (for Res and RoR) production capacity, reservoir capacity, inflow and inflow profiles per price areas from https://www.nve.no/energi/analyser-og-statistikk/vaerdatasett-for-kraftsystemmodellene/
- Detailed watercourse descriptions from https://www.nve.no/energi/energisystem/vannkraft/modell-av-det-norske-vannkraftsystemet/. The dataset exist in two DETD-formats (per EMPS area (also includes rest modules for small-scale hydro) or per watercourse), and simplified in an Excel-format. The dataset used in this demo is derived from the excel-format with some differences:
  - Every water balance has its own module (i.e. a module with both regulated and unregulated inflow is split into two modules).
  - It has pq-kurves and environmental restrictions
  - It has ramping restrictions for hydropower release (only used in market clearing).
- The inflow series for the detailed dataset can be found at https://www.nve.no/vann-og-vassdrag/hydrologiske-data/historiske-data/historiske-vannfoeringsdata-til-produksjonsplanlegging/.

In [50]:
```
# Read dataset for stochastic and market clearing models
sti_themadata = "data_fra_thema"
tst = JSON.parsefile(joinpath(sti_themadata, "dataset_thema_excl_hydro_nose.json")) # Euro
themastructure = getelements(tst)
tse = JSON.parsefile(joinpath(sti_themadata, "tidsserier_thema.json"))
themaseries = getelements(tse, sti_themadata)

dse = JSON.parsefile("data_fra_dynmodell/tidsserier_detd.json")
detdseries = getelements(dse);
dst = JSON.parsefile("data_fra_dynmodell/dataset_detd.json")
detdstructure = getelements(dst);

detailedelements = vcat(themaseries,themastructure,detdseries,detdstructure)
addscenariotimeperiod!(detailedelements, scenarioyearstart, scenarioyearstop);
```

Get water values for detailed hydro (DETD) from aggregated hydro (Thema)

- With different representations of watercourses in different problems, we need a mapping

In [51]:
```
# Mapping between aggregated and detailed storages
detailedrescopl = JSON.parsefile("data_fra_dynmodell/magasin_elspot1.json")

# Global energy equivalent detailed reservoirs
enekvglobaldict = JSON.parsefile("data_fra_dynmodell/magasin_enekvglobal.json") # TODO: on

# detailed dataset has reservoirs for SE4, aggregated does not, TODO: Improve aggregation/r
for k in keys(detailedrescopl)
    if detailedrescopl[k] == "SE4"
        detailedrescopl[k] = "SE3"
    end
end

# Get dictionary with each detailed reservoir and their water value for each scenario
# TODO: Detailed run-of-river reservoirs get water value from aggregated reservoir hydro
function getendvaluesdicts(endvaluesobjs, detailedrescopl::Dict, enekvglobaldict::Dict)
    endvaluesdicts = Dict[]
    for endvaluesobj in endvaluesobjs
        instance = [getinstancename(getid(obj)) for obj in endvaluesobj.objects]
        endvalues = endvaluesobj.values
        endvaluesdict = Dict(instance .=> endvalues)

        for (k,v) in detailedrescopl
            endvaluesdict["Reservoir_" * k] = endvaluesdict["Reservoir_" * v * "_hydro_res
        end
        push!(endvaluesdicts, endvaluesdict)
    end

    return endvaluesdicts
end
medendvaluesdicts = getendvaluesdicts(medendvaluesobjs, detailedrescopl, enekvglobaldict);
```

Stochastic subsystem models with Benders decomposition

- Each unique storage system is solved as a two-stage linear program with Benders decomposition
- The subsystems are optimized against exogen prices from the price prognosis scenarios
- We group storage systems into two. These are solved with different degree of detail
  - Med-term - mostly hydro
    - 52 week long horizon, weekly resolution, price from medium term price prognosis
  - Short-term - mostly batteries and PHS
    - Week long horizon, hourly resolution, price from short term price prognosis
- Outputs:
  - Cuts or storage values (battery or hydro) for use as end condition in market clearing problem

In [52]:
```
# Cut parameters
maxcuts = 13 # preallocate fixed number of cuts, no cut selection
lb = -1e5 # lower bound of the future value in the first iteration
reltol = 0.0001 # relative tolerance

# Parameters for stochastic subsystem problems
shorttotaldays = shortweeklength*7
medtotaldays = (medweeklength-2)*7 # we reuse prices for two weeks, so have to be two weeks
shortstartstorage = 50
medstartstorage = 65
medpriceslocal = convert(Vector{Dict}, medprices)
shortpriceslocal = convert(Vector{Dict}, shortprices)
storageinfo = (shortstartstorage, medstartstorage, medendvaluesdicts)
shortterminputs = (detailedelements, shorttotaldays, numscen, scenarioyearstart, phaseinof
medterminputs = (detailedelements, medtotaldays, numscen, scenarioyearstart, phaseinoffset
```

```
ustoragesystemobjects = []
ushorts = []
# Make modelobjects for short-term subsystems
@time makemastersubobjects!(shortterminputs, ustoragesystemobjects, ushorts)
# Make modelobjects for medium-term subsystems
@time makemastersubobjects!(medterminputs, ustoragesystemobjects, ushorts)

# Distribute subsystems with inputs and outputs on different cores
storagesystemobjects, shorts = distribute_subsystems(ustoragesystemobjects, ushorts)
masters = distribute([HiGHS_Prob() for i in 1:length(storagesystemobjects)], storagesystem
subs = distribute([[] for i in 1:length(storagesystemobjects)], storagesystemobjects)
states = distribute([Dict{StateVariableInfo, Float64}() for i in 1:length(storagesystemobj
cuts = distribute([SimpleSingleCuts() for i in 1:length(storagesystemobjects)], storagesys
storagesystems = distribute([Dict() for i in 1:length(storagesystemobjects)], storagesyste

# Initialize subsystem problems and run for first time step. Run subsystems in parallell
@time pl_stochastic_init!(numcores, storagesystemobjects, shorts, masters, subs, states, c
```

```
  6.170632 seconds (15.41 M allocations: 660.030 MiB, 55.75% compilation time)
  3.067123 seconds (12.57 M allocations: 505.485 MiB, 2.17% compilation time)
  6.781912 seconds (521.16 k allocations: 17.477 MiB, 0.94% compilation time)
```

Out[52]:
```
Task (done) @0x00000002700d6ca0
```

Market clearing problem

- Deterministic LP
- Two days, two-hour resolution, full detail (hydro and thermal)
- Inputs:
  - Detailed power market representation
  - Water values and battery storage values from stochastic subsystem problems
  - Thermal end condition from short term price prognosis model
- Outputs:
  - Two day detailed power market simulation (price, production, reservoir etc...)
  - Start state for next time step (reservoirs and other state variables)

In [53]:
```
# Bring data to local core
cutslocal = convert(Vector{SimpleSingleCuts}, cuts)
nonstoragestateslocal = convert(Vector{Dict}, nonstoragestates)

# Initialize market clearing problem and run for first time step
@time clearing, nonstoragestatesmean, clearingendvaluesdict, varendperiod = clearing_init(
```

```
  9.986348 seconds (8.29 M allocations: 455.151 MiB, 8.58% gc time, 44.25% compilation tim
e)
```

In [54]:
```
# Initialize start states for next time step, also mapping to Thema storages and max capac
startstates = startstates_init(clearing, detailedrescopl, enekvglobaldict, longprobs[1], t
```

Initialize and collect results: Prices and start states (e.g. reservoirs)

In [55]:
```
# Initialize and collect prices and start states
price = Dict()
powerhorizonix = argmax(getnumperiods(h) for h in clearing.horizons)
getareaprices!(price, clearing, clearing.horizons[powerhorizonix], tnormal)
areanames = price["names"]
ix = collect(price["steprange"])
pricematrix = copy(price["matrix"])

statenames = collect(keys(startstates))
statematrix = collect(values(startstates));
```

Collect more detailed results

- Prices, supply, demand, transmission and hydro storage levels
- TODO: Customize results more, now assumes same time resolution for all hydropower reservoirs
- TODO: Convert hydro reservoir levels to energy

In [57]:
```
numperiods_powerhorizon = 24
numperiods_hydrohorizon = 8
periodduration_power = Millisecond(Hour(2));
periodduration_hydro = Millisecond(Hour(6));
clearingobjects = Dict(zip([getid(obj) for obj in clearing.objects],clearing.objects))
# resultobjects = getpowerobjects(clearingobjects,["NO2"]); # only collect results for one
resultobjects = clearing.objects # collect results for all areas
prices, rhstermvalues, production, consumption, hydrolevels, powerbalances, rhsterms, rhst
```

Simulate next time steps (16 steps = 32 days)

- Simulate next time steps, store results and plot results

In [58]:
```
# Only update medterm and longterm every 8 days (med/long prices and med/long watervalues
skipmed = Millisecond(Day(2))

steps = 16;
# steps = (getisoyearstart(scenarioyearstop) - getisoyearstart(scenarioyearstart)).value/M
```

In [59]:
```
step = 2
tnormal += Day(2)
tphasein = PhaseinTwoTime(getdatatime(tnormal), getscenariotime(tnormal), getscenariotime(
display(tnormal)

totaltime = @elapsed while step <= steps

    # Deterministic long/mid/short - calculate scenarioprices
    @time pl_prognosis!(numcores, longprobs, medprobs, shortprobs, medprices, shortprices,

    # Stochastic sub systems - calculate storage value
    if skipmed.value == 0
        medpriceslocal = convert(Vector{Dict}, medprices)
        medendvaluesdicts = getendvaluesdicts(medendvaluesobjs, detailedrescopl, enekvgloba
    end
    shortpriceslocal = convert(Vector{Dict}, shortprices)

    @time pl_stochastic!(numcores, masters, subs, states, cuts, startstates, medpricesloca

    # Market clearing
    cutslocal = convert(Vector{SimpleSingleCuts}, cuts)
    nonstoragestateslocal = convert(Vector{Dict}, nonstoragestates)

    # Try reusing cuts in market clearing, if non-optimal solution retry with fresh cuts
    try
        @time clearing!(clearing, tnormal, startstates, cutslocal, clearingendvaluesdict,

        updateareaprices!(price, clearing, clearing.horizons[powerhorizonix], tnormal)
        ix = vcat(ix, collect(price["steprange"]))
        pricematrix = vcat(pricematrix, price["matrix"])
        statematrix = hcat(statematrix, collect(values(startstates)))

        prices, rhstermvalues, production, consumption, hydrolevels = update_results(clear

        step += 1
        tnormal += Day(2)
        tphasein = PhaseinTwoTime(getdatatime(tnormal), getscenariotime(tnormal), getscena
        display(tnormal)

        skipmed += Millisecond(Day(2))
        if skipmed > Millisecond(Day(6))
            skipmed = Millisecond(0)
```

```
        end
    catch
        println("Non-optimal market clearing, calculating new cuts for time step (could als
        skipmed = Millisecond(0)
    end
end

display(string("The simulation took: ", totaltime/60, " minutes"))
display(string("Time usage per timestep: ", totaltime/steps, " seconds"))
```

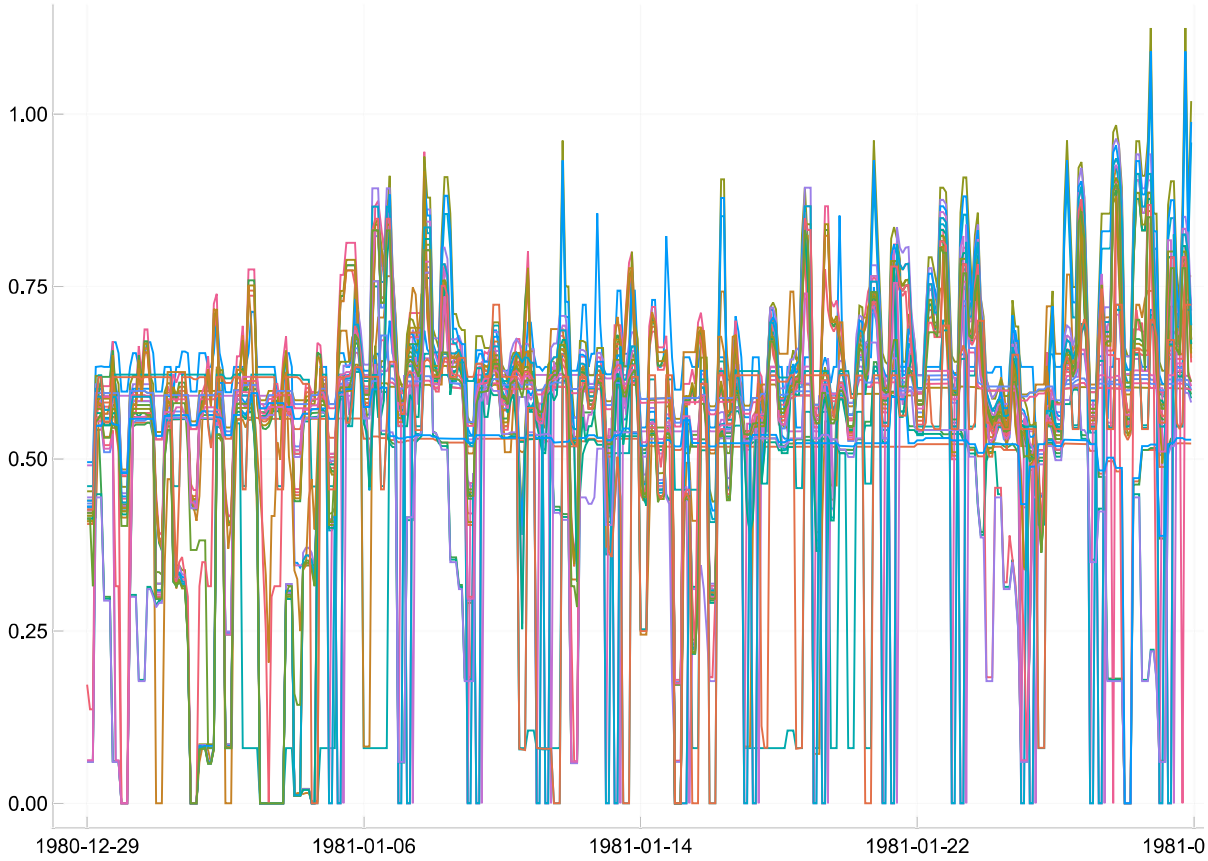
```
FixedDataTwoTime(DateTime("2024-12-30T00:00:00"), DateTime("1980-12-31T00:00:00"))
  2.599146 seconds (184.14 k allocations: 10.657 MiB, 2.30% compilation time)
  0.798966 seconds (636.98 k allocations: 22.807 MiB, 7.64% compilation time)
 10.901186 seconds (606.67 k allocations: 32.691 MiB, 1.73% compilation time)
FixedDataTwoTime(DateTime("2024-12-30T00:00:00"), DateTime("1981-01-02T00:00:00"))
  2.386047 seconds (75.56 k allocations: 5.090 MiB)
  0.197289 seconds (526.52 k allocations: 17.159 MiB)
 20.540372 seconds (487.76 k allocations: 26.412 MiB)
FixedDataTwoTime(DateTime("2024-12-30T00:00:00"), DateTime("1981-01-04T00:00:00"))
  2.701029 seconds (75.56 k allocations: 5.090 MiB)
  0.198427 seconds (526.52 k allocations: 17.160 MiB)
 14.520283 seconds (487.76 k allocations: 26.412 MiB)
FixedDataTwoTime(DateTime("2024-12-30T00:00:00"), DateTime("1981-01-06T00:00:00"))
  4.763082 seconds (75.57 k allocations: 5.094 MiB)
  3.040720 seconds (527.90 k allocations: 17.229 MiB)
 16.442967 seconds (487.76 k allocations: 26.412 MiB)
FixedDataTwoTime(DateTime("2024-12-30T00:00:00"), DateTime("1981-01-08T00:00:00"))
  1.992946 seconds (75.55 k allocations: 5.091 MiB)
  0.196527 seconds (526.53 k allocations: 17.160 MiB)
 11.050047 seconds (487.76 k allocations: 26.412 MiB)
FixedDataTwoTime(DateTime("2024-12-30T00:00:00"), DateTime("1981-01-10T00:00:00"))
  1.839467 seconds (75.55 k allocations: 5.091 MiB)
  0.195650 seconds (526.53 k allocations: 17.160 MiB)
 20.980937 seconds (487.76 k allocations: 26.412 MiB)
FixedDataTwoTime(DateTime("2024-12-30T00:00:00"), DateTime("1981-01-12T00:00:00"))
  2.249780 seconds (75.56 k allocations: 5.091 MiB)
  0.195668 seconds (526.54 k allocations: 17.162 MiB)
 23.974399 seconds (487.76 k allocations: 26.412 MiB)
FixedDataTwoTime(DateTime("2024-12-30T00:00:00"), DateTime("1981-01-14T00:00:00"))
  4.596997 seconds (75.57 k allocations: 5.094 MiB)
  2.856693 seconds (526.55 k allocations: 17.162 MiB)
 19.119443 seconds (487.76 k allocations: 26.412 MiB)
FixedDataTwoTime(DateTime("2024-12-30T00:00:00"), DateTime("1981-01-16T00:00:00"))
  3.253460 seconds (75.60 k allocations: 5.095 MiB)
  0.198960 seconds (526.53 k allocations: 17.161 MiB)
 20.484803 seconds (487.76 k allocations: 26.412 MiB)
FixedDataTwoTime(DateTime("2024-12-30T00:00:00"), DateTime("1981-01-18T00:00:00"))
  3.132229 seconds (75.59 k allocations: 5.092 MiB)
  0.201911 seconds (526.53 k allocations: 17.160 MiB)
 11.989044 seconds (487.76 k allocations: 26.412 MiB)
FixedDataTwoTime(DateTime("2024-12-30T00:00:00"), DateTime("1981-01-20T00:00:00"))
  3.326676 seconds (76.22 k allocations: 5.140 MiB)
  0.197215 seconds (526.53 k allocations: 17.161 MiB)
 12.954177 seconds (487.76 k allocations: 26.412 MiB)
FixedDataTwoTime(DateTime("2024-12-30T00:00:00"), DateTime("1981-01-22T00:00:00"))
  5.817413 seconds (75.61 k allocations: 5.096 MiB)
  2.747081 seconds (526.55 k allocations: 17.165 MiB)
 13.105605 seconds (487.76 k allocations: 26.412 MiB)
FixedDataTwoTime(DateTime("2024-12-30T00:00:00"), DateTime("1981-01-24T00:00:00"))
  3.241043 seconds (75.59 k allocations: 5.095 MiB)
  0.192507 seconds (526.53 k allocations: 17.161 MiB)
 17.919673 seconds (487.76 k allocations: 26.412 MiB)
FixedDataTwoTime(DateTime("2024-12-30T00:00:00"), DateTime("1981-01-26T00:00:00"))
  2.775003 seconds (75.58 k allocations: 5.095 MiB)
  0.195233 seconds (526.53 k allocations: 17.161 MiB)
 20.522320 seconds (487.76 k allocations: 26.412 MiB)
FixedDataTwoTime(DateTime("2024-12-30T00:00:00"), DateTime("1981-01-28T00:00:00"))
```

```
  1.775285 seconds (75.55 k allocations: 5.091 MiB)
  0.190121 seconds (526.53 k allocations: 17.160 MiB)
 15.787052 seconds (487.76 k allocations: 26.412 MiB)
FixedDataTwoTime(DateTime("2024-12-30T00:00:00"), DateTime("1981-01-30T00:00:00"))
"The simulation took: 5.236222493333333 minutes"
"Time usage per timestep: 19.63583435 seconds"
```

Plot resulting prices

In [60]:
```
plot(ix,pricematrix,label=reshape(areanames, 1, length(areanames)),size=(800,500),legend=:
```

Out[60]:



Comments:

- Throughout the testing we have achieved the wanted price volatility in the thermal dominated part of the dataset (Western Europe). On the other hand, the Nordics have had very flat prices due to too much flexibility in the hydropower system. In this demo we have therefore added hydropower production ramping restrictions in an attempt to reduce the flexibility of the run-of-river hydropower plants. This results in much more price volatiliy, but at a big computational cost.
- Ramping restrictions on transmission lines has the same effect. Without ramping restrictions (hydro and transmission) the computational time is down to around 9 seconds in total per time step. This is promising considering the big dataset, and the list of possible optimization we have in mind. It is also always possible to clear the market for 24 hours instead of 48 hours like now, which would reduce the computational time substantially. It is also interesting what these computational times would be with a commercial solver.
- We will try different configurations of ramping restrictions, and also test if time delays can achieve the same effects at a lower computation cost. Considering unavailability of hydropower or reserve market obligations, should also decrease the flexibility of the hydropower system.

Postprocess detailed results

- Combine fixed contributions (e.g. wind, solar and demand) together with supply and demand variables
- Make time axis for price, supply/demand and reservoir levels

In [61]:
```
# Only keep rhsterms that have at least one value (TODO: Do the same for sypply and demands
rhstermtotals = dropdims(sum(rhstermvalues,dims=1),dims=1)
rhstermsupplyidx = []
rhstermdemandidx = []

for k in 1:length(rhsterms)
    if rhstermtotals[k] > 0
        push!(rhstermsupplyidx, k)
    elseif rhstermtotals[k] < 0
        push!(rhstermdemandidx, k)
    end
end

# Put rhsterms together with supplies and demands
rhstermsupplyvalues = rhstermvalues[:,rhstermsupplyidx]
rhstermdemandvalues = rhstermvalues[:,rhstermdemandidx]*-1

rhstermsupplynames = [getinstancename(rhsterm) for rhsterm in rhsterms[rhstermsupplyidx]]
rhstermsupplybalancenames = [split(getinstancename(r), "PowerBalance_")[2] for r in rhsterm
rhstermdemandnames = [getinstancename(rhsterm) for rhsterm in rhsterms[rhstermdemandidx]]
rhstermdemandbalancenames = [split(getinstancename(r), "PowerBalance_")[2] for r in rhsterm

supplynames = [[getinstancename(plant) for plant in plants];rhstermsupplynames]
supplybalancenames = [[split(getinstancename(p), "PowerBalance_")[2] for p in plantbalance
supplyvalues = hcat(production,rhstermsupplyvalues)

demandnames = [[getinstancename(demand) for demand in demands];rhstermdemandnames]
demandbalancenames = [[split(getinstancename(p), "PowerBalance_")[2] for p in demandbalanc
demandvalues = hcat(consumption, rhstermdemandvalues)

# Prepare for plotting results
hydronames = [getinstancename(hydro) for hydro in hydrostorages]
powerbalancenames = [split(getinstancename(powerbalance), "PowerBalance_")[2] for powerbal

# Time
x1 = [getisoyearstart(scenarioyearstart) + periodduration_power*(t-1) for t in 1:first(siz
x2 = [getisoyearstart(scenarioyearstart) + periodduration_hydro*(t-1) for t in 1:first(siz
```

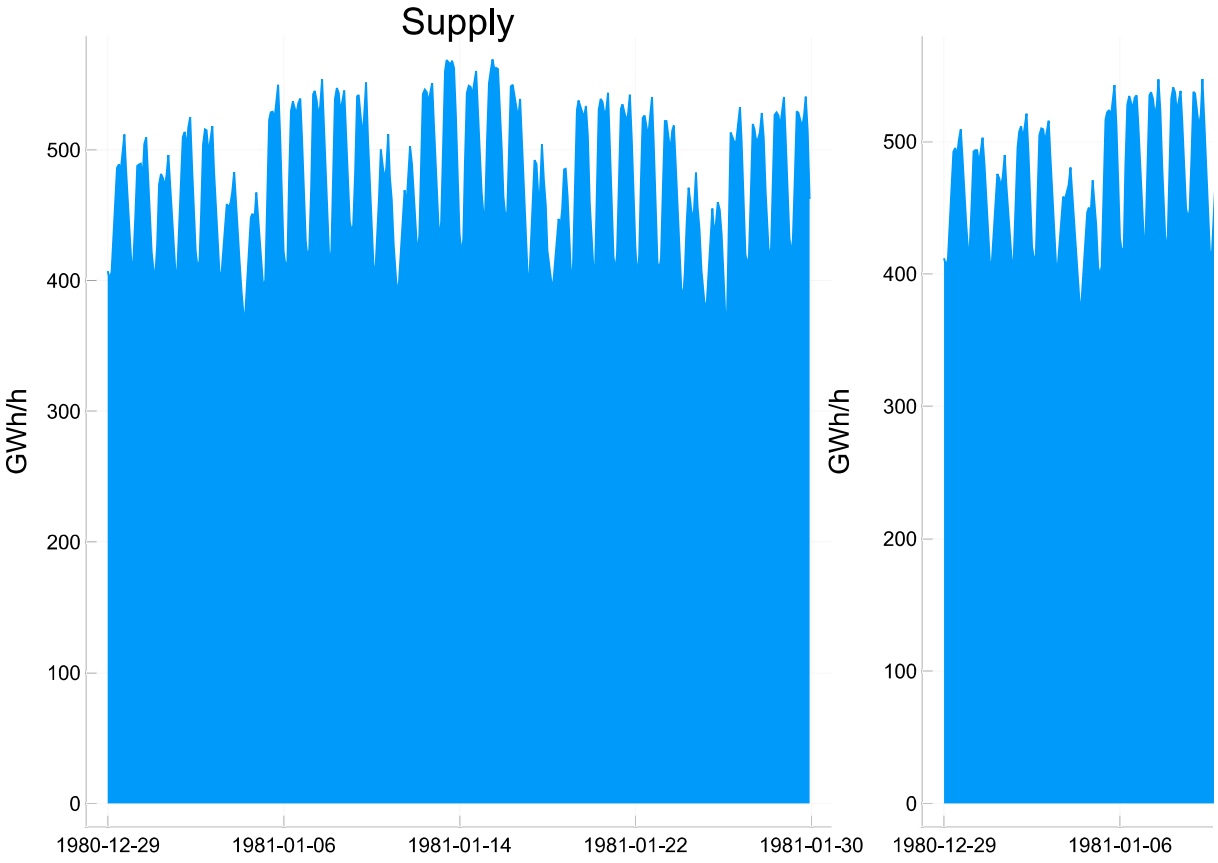
In [62]:
```
# # Store results
# data = Dict()
# data["areanames"] = areanames
# data["pricematrix"] = pricematrix
# data["priceindex"] = ix

# data["statenames"] = statenames
# data["statematrix"] = transpose(statematrix)
# data["stateindex"] = [getisoyearstart(scenarioyearstart) + Day(2*(i-1)) for i in 1:first

# data["supplyvalues"] = supplyvalues
# data["supplynames"] = supplynames
# data["supplybalancenames"] = supplybalancenames

# open("JulES_2030_81_10_64.json", "w") do f
#     write(f, JSON.json(data))
# end

# areaprices = rename!(DataFrame(prices, :auto),powerbalancenames)
# areaprices[!,:time] = x1
# CSV.write("JulES_results\\prices.csv", areaprices)
```

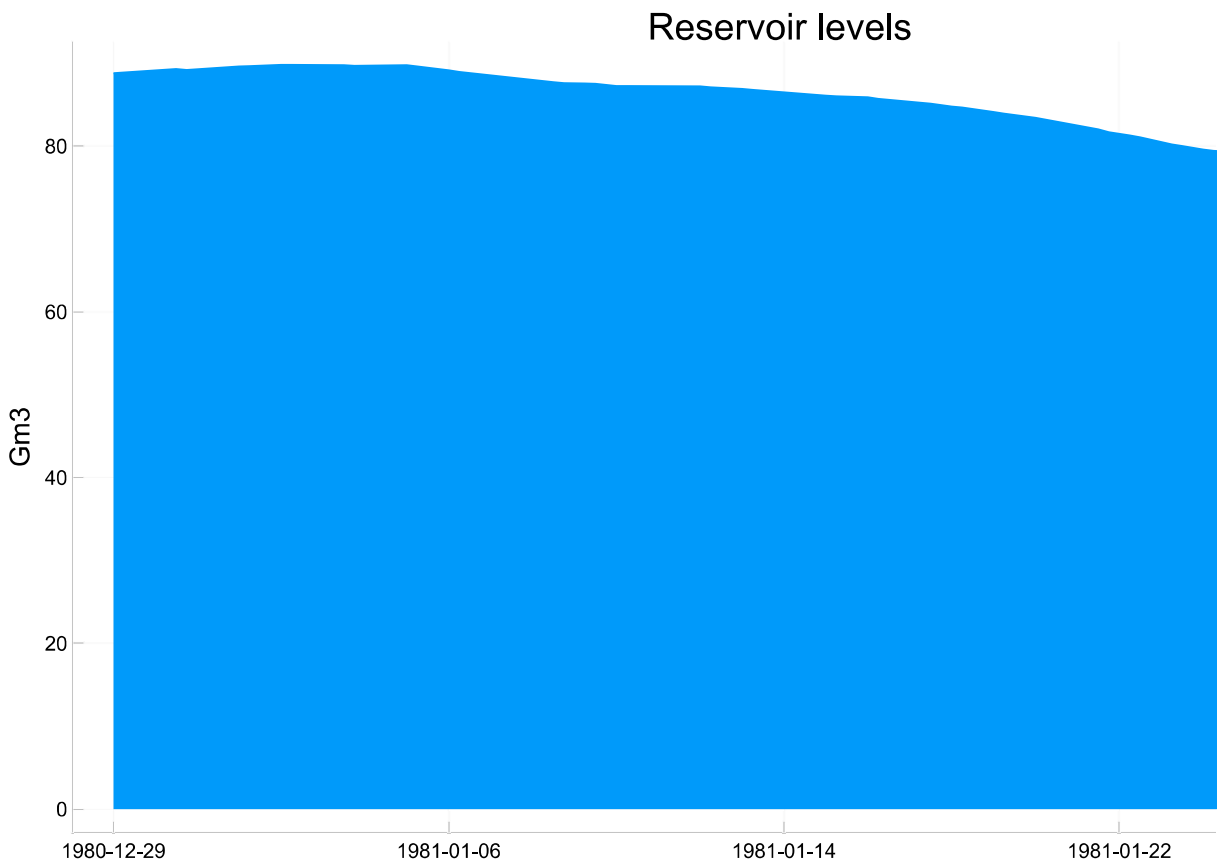
```
# demand = rename!(DataFrame(demandvalues, :auto),demandnames)
# demand[!,:time] = x1
# demand = stack(demand,Not(:time))
# demandcopl = DataFrame(variable=demandnames, area=demandbalancenames)
# demand = leftjoin(demand, demandcopl, on=:variable)
# CSV.write("JulES_results\\demand.csv", demand)

# supply = rename!(DataFrame(supplyvalues, :auto),supplynames)
# supply[!,:time] = x1
# supply = stack(supply,Not(:time))
# supplycopl = DataFrame(variable=supplynames, area=supplybalancenames)
# supply = leftjoin(supply, supplycopl, on=:variable)
# CSV.write("JulES_results\\supply.csv", supply)

# hydro = rename!(DataFrame(hydrolevels, :auto),hydronames)
# hydro[!,:time] = x2
# CSV.write("JulES_results\\hydro.csv", hydro);
```

In [63]:

```
# Plot prices
display(plot(x1, prices, labels=reshape(powerbalancenames,1,length(powerbalancenames)), si

# # Plot supplies and demands
# supplychart = areaplot(x1, supplyvalues,labels=reshape(supplynames,1,length(supplynames),
# demandchart = areaplot(x1, demandvalues,labels=reshape(demandnames,1,length(demandnames),
# display(plot([supplychart,demandchart]...,layout=(1,2),size=(1600,500)))
supplychart = areaplot(x1, sum(supplyvalues,dims=2),title="Supply", ylabel = "GWh/h")
demandchart = areaplot(x1, sum(demandvalues,dims=2),title="Demand", ylabel = "GWh/h")
display(plot([supplychart,demandchart]...,layout=(1,2),size=(900,500)))

# Plot storages
# display(areaplot(x2, hydrolevels,labels=reshape(hydronames,1,length(hydronames)),size=(80
display(areaplot(x2, dropdims(sum(hydrolevels,dims=2),dims=2),labels="Total reservoirs",si


# Plot list of yearly mean production and demand for each supply/demand
meandemand = dropdims(mean(demandvalues,dims=1),dims=1)
meanproduction = dropdims(mean(supplyvalues,dims=1),dims=1)
supplydf = sort(DataFrame(Supplyname = supplynames, Yearly_supply_TWh = meanproduction*8.7
demanddf = sort(DataFrame(Demandname = demandnames, Yearly_demand_TWh = meandemand*8.76),[
supplydf[!,:ID] = collect(1:length(supplynames))
demanddf[!,:ID] = collect(1:length(demandnames))
joineddf = select!(outerjoin(supplydf,demanddf;on=:ID),Not(:ID))
# show(joineddf,allcols=true, allrows=true)

# Check that total supply equals total demand
show(combine(joineddf, [:Yearly_supply_TWh, :Yearly_demand_TWh] .=> sum∘skipmissing))
```


Prices
€/MWh
1.00
0.75
0.50
0.25
0.00
1980-12-29
1981-01-06
1981-01-14
1981-01-22


Supply
GWh/h
500
400
300
200
100
0
1980-12-29
1981-01-06
1981-01-14
1981-01-22
1981-01-30
GWh/h
500
400
300
200
100
0
1980-12-29
1981-01-06



1×2 DataFrame

Row	Yearly_supply_TWh_sum_skipmissing	Yearly_demand_TWh_sum_skipmissing
	Float64	Float64
1	4179.13	4175.72

- Yearly_supply_TWh and Yearly_demand_TWh is the mean production timed with 8736.
- Transmission into the area is added to supply, while transmission out is added to demand.
- The reason why the supply does not match the demand is that the filtering does not split up watercourses where hydropower plants are in different areas. The supply side (of NO2) therefore contains 14 hydropower plants in NO1 and NO5.

In [ ]: