Portfolio Management and Optimization with PLEXOS®

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Content

1. Coping with Uncertainty and Risk
2. Scenario Analysis and Monte Carlo Simulations
3. Multi-stage Stochastic Optimization in PLEXOS for a Robust Portfolio Optimization
ON JUNE 16th something very peculiar happened in Germany’s electricity market. The wholesale price of electricity fell to minus €100 per megawatt hour (MWh). That is, generating companies were having to pay the managers of the grid to take their electricity. It was a bright, breezy Sunday. Demand was low. Between 2pm and 3pm, solar and wind generators produced 28.9 gigawatts (GW) of power, more than half the total. The grid at that time could not cope with more than 45GW without becoming unstable. At the peak, total generation was over 51GW; so prices went negative to encourage cutbacks and protect the grid from overloading.

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“How excess supply plus depressed demand equals lower prices”

“Electricity prices have fallen from over €80 per MWh at peak hours in Germany in 2008 to just €38 per MWh now. These are wholesale prices; residential prices are €285 per MWh, some of the highest in the world, partly because they include subsidies for renewables that are one-and-a-half times, per unit of energy, the power price itself. As wholesale prices fall, so does the profitability of power plants. Bloomberg New Energy Finance (BNEF), a data-provider, reckons that 30-40% of RWE’s conventional power stations are losing money. But that is only the half of it. Renewables have not just put pressure on margins. They have transformed the established business model for utilities.”
Europe’s electricity providers face an existential threat
(The Economist 12/10/2013)

New Era
The decline of Europe’s utilities during the last few years has certainly been astonishing. At their peak in 2008, the top 20 energy utilities were worth roughly €1 trillion ($1.3 trillion). Now, less than half that.

Under the “old” system, electricity prices spiked during the middle of the day and early evening, falling at night with lower demand. So, companies made all their money during peak periods.

Now the middle of the day belongs to solar generation that has competed away the price spike.

In Germany in 2008, according to the Fraunhofer Institute for Solar Energy Systems, peak-hour prices were €14 per MWh above baseload prices. In the first six months of 2013, this premium was €3 per MWh.

So not only have average electricity prices fallen by half since 2008, but the peak premium has also fallen by almost 80%!!
Historical price analysis slowly becoming less relevant

- Fundamental changes in the energy markets are already effecting prices
  - Changing government policies (EMR)
  - Change in market design (coupling of markets)
  - Renewable Integration/Subsidies
  - Drop in energy demand and growth due to economic crisis
  - Falling CO₂ price
  - Spark spreads going to negative and falling (expensive Gas)
  - Dark spreads going positive (cheap imported coal)

- What do we have to consider next?
  - Demand Side Management
  - Energy Storage technologies
  - Capacity markets or more importance on reserves and balancing
  - Increased electrification of rail networks
  - Government legislation and policies

- Understanding renewables profiles and potential variations is becoming more critical in forecasting daily prices both for best hedging and portfolio optimisation.
Coping with uncertainty and Risk

**Forecasting** is a process that inherently carries **uncertainty**.

- PLEXOS® offers three distinct approaches to coping with uncertainty:
  - Scenario analysis
  - Monte Carlo simulation
  - Stochastic optimisation

- In PLEXOS® any parameter can easily have uncertainty applied to it. Common parameters to undertake analysis of include:
  - Load
  - Fuel and emission prices
  - Electricity prices (if using price as an input)
  - Ancillary services prices
  - Hydro inflows
  - Wind energy, etc

- These parameters (**Variables**) can also be correlated
  - A high wind generation/speed might be associated with a high demand sample
Volatility in DA/ID power Markets

Wind power is unpredictable by nature. Due to its increased volatility within day, imbalances between day-ahead contracts and produced volume often need to be offset within very short time intervals.

Apart from the **Day-ahead** market, **Intraday** and **Regulating** power markets are becoming increasingly important for the development and integration of Wind/PV power in the power systems.
How does wind and solar power influence the power price on the spot market?

The impact of wind power generation on the day-ahead spot prices can be quite substantial, something that have been reported in a number of related studies.

Particularly, adding wind into the power mix has a significant influence on the resulting price of electricity, the so called **Merit Order Effect (MOE)**.

Wind power does contribute to the reduction in prices but also interconnector capacities play a very significant role in bringing the price to zero at time.
How does wind power and photovoltaic influence the power price on the spot market?

In general, Wind & PV power influence prices on the spot market in two ways:

A) Wind/PV power normally has a low marginal cost (zero fuel costs) and therefore enters near the bottom of the supply (stack) curve. Graphically, this shifts the supply curve to the right (see next Figure), resulting in a lower power price, depending on the price elasticity of the power demand. In general, the price of power is expected to be lower during periods with high wind than in periods with low wind. This is called the ‘Merit Order Effect’.
How does wind power and photovoltaic influence the power price on the spot market?

The way in which Wind/PV power integration influences the power spot price due to its low marginal cost.
B) There may be congestion in power transmission, especially during periods with high Wind power generation. Thus, if the available transmission capacity cannot cope with the required power export, the supply area is separated from the rest of the power market (market splitting) and constitutes its own pricing area. With an excess supply of power in this area, conventional power plants have to reduce their production, since it is generally not economically or environmentally desirable to limit the power production of wind. In most cases, this will lead to a lower power price in the sub-market.
How does wind power and photovoltaic influence the power price on the spot market?

MIBEL Price Collapse & Market Splitting - 31/10/2010 - PLEXOS®
How does wind power and photovoltaic influence the power price on the spot market?

The impact of wind power on market prices depends on the time of the day.

If there is **plenty of wind power** at midday, during the peak power demand, most of the available generation will be used. This implies that we are at the steep part of the supply curve (see next figure) and, consequently, wind power will have a **strong impact**, reducing the spot power price significantly (from **Price A** to **Price B**).

But if there is plenty of wind-produced electricity **during the night**, when **power demand is low** and most power is produced on base load plants, we are at the flat part of the supply curve and consequently **the impact of wind power on the spot price is low**.
How does wind power and photovoltaic influence the power price on the spot market?
How does wind power and photovoltaic influence the power price on the spot market?

- Many studies have shown that an increase in amount of wind power reduces the periods of constant production and the duration of these periods.
- The capacity factor of units with low start-up and turn down performances and high minimum stable level will decrease more than the capacity factor of units with high start and turn down performance and/or low minimum stable level.
- With increased wind power volatile fed in the power price becomes increasingly volatile as well.
- While the short term effect of wind is lowering prices, in the long term there is an effect on the conventional capacity as well.
- Therefore, the result of the RES-E integration with a relatively low capacity credit is an increase in peak load capacity and decrease in base load capacity.
- The slope of the merit-order curve will also change in the long run due to this.
How does wind power and photovoltaic influence the power price on the spot market?

- In general, an increased penetration of wind power reduces wholesale spot prices.
- In countries, where the target is to have a high percentage of the electricity consumption from Wind/PV, there will be more instances of zero spot prices.
- This will have an effect on new generation investments by making investments in future capacities less attractive.
- The share of RES will play an crucial role in future development of the market structure.
- During periods of low demand, the technology that sets the price in the wholesale market is usually hard coal in most European countries. It has been observed that Wind replaces hard coal power plants during hours of low demand and gas fired power plants during hours of high demand.
- For the time being, Lignite and nuclear have no MOE so Gas and hard coal had the highest MOE.

MOE effect has been reported to range from 3 to 23 €/MWh.
Scenario objects allow data to be labelled with a particular scenario name. Scenarios are created in the same ways as other objects. Once created, any property can be tagged with that scenario name. **Model** objects (the objects that are executed during a simulation) have a **Scenarios** collection. Adding a Scenario to this collection instructs PLEXOS to use all the properties tagged with that scenario name as well as all properties that have no tag. Data from Scenarios overrides untagged data.

Where two Scenarios specify values for the same datum in the same time period, the Scenarios are read in alphabetical order. Although this behaviour can be overridden using the Priority property.

Selecting a Scenario object in the PLEXOS interface and the Properties window displays all the properties in the database that are tagged with that Scenarios name. Deleting a Scenario object causes all data associated with that Scenario to be deleted too.
Stochastic Programming - Monte Carlo vs. Optimisation

- Monte Carlo simulation (Parallel Option)
  - Assumes perfect foresight for each stochastic sample
  - PLEXOS then computes the optimal decision for each of a number of possible stochastic samples independently

- Stochastic Optimisation
  - Simultaneously considers all the possible stochastic samples and associated probabilities
  - PLEXOS computes a single optimal decision that is best hedged for the uncertainty represented by the stochastic samples
Stochastic Optimization Motivation

- **Fix perfect foresight issue**
  - Monte Carlo simulation can tell us what the optimal decision is for each of a number of possible outcomes assuming perfect foresight for each scenario independently;
  - It cannot answer the question: what decision should I make now given the uncertainty in the inputs?

- **Stochastic Programming**
  - The goal of SO is to find some policy that is **feasible and optimal for all** (or almost all) the possible data instances and maximize the expectation of some function of the decisions and the random variables

- **SO can be linear (Stochastic Linear Programming) or integer (Stochastic Integer Programming)**
SO Background

- The most widely applied and studied stochastic programming models are two-stage linear programs.
- Here the decision maker takes some action in the first stage, after which a random event occurs affecting the outcome of the first-stage decision.
- A recourse decision can then be made in the second stage that compensates for any bad effects that might have been experienced as a result of the first-stage decision.
- The optimal policy from such a model is a single first-stage policy and a collection of recourse decisions (a decision rule) defining which second-stage action should be taken in response to each random outcome.
Stochastic Integer Programming (SIP)

- Where the first (or second) stage decisions must take integer values we have a stochastic integer programming (SIP) problem.
- SIP problems are difficult to solve in general.
- Assuming integer first-stage decisions (e.g. how many generators of type x to build) we want to find a solution that minimises the total cost (or maximise the profit) of the first and second stage decisions.
- A number of solution approaches have been suggested in the literature.
- PLEXOS® uses scenario-wise decomposition...
Stochastic Variables

- We assume that uncertain inputs have a definable probability distribution
- Number of samples $S$ limited only by computing memory
- First-stage variables depend on the simulation phase
- Remainder of the formulation is repeated $S$ times
2-stage SIP Formulation

- \( x \) and \( y \) represents the first and second-stage decisions resp.
- \( \omega \) represents the uncertain data
- \((q, W, h, T)\) are a realisation of the random data
- \( R \) and \( Z \) denote reals and integers respectively

\[
\begin{align*}
\min & \quad c^T x + \mathbb{E}[Q(x, \omega)] \\
\text{s.t.} & \quad A x = b \\
& \quad x \in R_+^{n_1-p_1} \times Z_+^{p_1}
\end{align*}
\]

where

\[
Q(x, \omega) := \min q^T y
\]

\[
\text{s.t.} \quad W y = h - T x \\
& \quad y \in R_+^{n_2-p_2} \times Z_+^{p_2}
\]
Scenario-wise Decomposition for 2-Stage SIP

- Assume the distribution $\omega$ of uncertain inputs can be evaluated as discrete scenarios $\{\omega_1, \omega_1, \ldots, \omega_S\}$ having probabilities $\{p_1, p_2, \ldots, p_S\}$ the two-stage SIP can be formulated:

$$\text{Minimise } \sum_{s=1}^{S} p_s (c^T x_s + q_s^T y_s)$$

subject to

$$A x_s = b \quad s = 1, \ldots, S$$
$$T_s x_s + W_s y_s = h_s \quad s = 1, \ldots, S$$
$$x_s \in R^{n_1-p_1}_+ \times Z^{p_1}_+ \quad s = 1, \ldots, S$$
$$y_s \in R^{n_2-p_2}_+ \times Z^{p_2}_+ \quad s = 1, \ldots, S$$

$x_1 = x_2 = \cdots = x_S$
Scenario-wise Decomposition (cont)

- Copies of the first-stage variable have been introduced for each scenario.
- The last constraint, known as **non-anticipativity constraints** guarantee that the first-stage variables are identical across the different scenarios.
- In other words, there are certain decisions that must be made ‘now’ and some that are made ‘later’ and the non-anticipativity constraints ensure that we do not anticipate what we cannot see coming when optimising those ‘now’ decisions.
Scenario-Wise Decomposition

Example:

- **Three Wind Periods:**
  - Morning
  - Mid-day
  - Night

- **If wind is low in any period:**
  - 50% chance that wind remains low
  - 50% chance it increases to mid

- **If wind is mid in any period:**
  - 33% chance decreases to low
  - 33% chance it remains mid
  - 33% chance it increases to high

- **If wind is high in any period:**
  - 50% chance that wind remains high
  - 50% chance it decreases to mid

- **17 possible paths, or “scenarios”**
Paths are “decomposed” into discrete scenarios with discrete probabilities.

Scenario wise decomposition assigns probabilities to each scenario:
- Similar paths are combined
- Unlikely paths are removed
- Probabilities are recomputed

For example, it is unlikely that wind can be high during mornings (H1) and, therefore unlikely to be low during the day (M2).
Scenario-Wise Decomposition – Sample Reduction

Initial Problem

Scenarios

Sample Reduction

Initial "high"

Initial "mid"

Initial "low"
In some cases, decision making problems comprise more than two stages. This fact motivates the use of **multi-stage stochastic programming** when it is possible that observations are made at **T different stages**. Stages correspond to time instances when some information is revealed (or where uncertainty partially or totally vanishes) and a decision can be made.

The amount of information available to the decision maker is usually different from stage to stage.
Multistage Stochastic Optimization

This decision framework is conveniently visualized through a scenario tree. The nodes represent states of the problem at a particular instant: where the decisions are made. In the first node, called “The Root”, the first stage decisions are made. The nodes connected to the root node are the second stage nodes and represents the points where the second stages decisions are made. The number of nodes in the last stage equals the number of scenarios. The branches are different realizations of the random variables.
Multi-Stage Stochastic Optimization

100 Simulations in DAM
- DA Hourly Wind and Load
- 1-day Co-optimization
- 1-Day Look-ahead
- Hourly Unit Commitment (long-run generators)

100 Simulations in HAM
- HA Wind and Load
- 5-hour Co-Optimization
- Hourly Unit Commitment (long, medium, short run generators)

100 Simulations in RT
- Actual 5min Wind and Load
- 65min co-optimization
Multistage - Sampling Methods example

For example if the user has these samples in a csv:

<table>
<thead>
<tr>
<th></th>
<th>A1</th>
<th>B1</th>
<th>C1</th>
</tr>
</thead>
<tbody>
<tr>
<td>A2</td>
<td>B2</td>
<td>C2</td>
<td></td>
</tr>
<tr>
<td>A3</td>
<td>B3</td>
<td>C3</td>
<td></td>
</tr>
</tbody>
</table>

The user can create automatically all the possible combinations of samples to reproduce the following tree:

The number of possible combination is: \((\text{Branches per Stages})^{\text{NStages}}\)

This is equal to 27 samples in this example:
Two Stages vs Multi-Stage

Two Stages Multi-Period

Usually represented as a fan tree:

Two Stages means: take the optimal policy based on that information will not be revealed at some stage in the future.
The decision variables per scenario are equal across the periods

Multi-Stage

In Multistage different optimal policy trajectories can be obtained, since the optimal trajectory will depend on the information revealed through time.

The decision variables are different according to the node they belong.

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3rd Intelligent Hedging & Portfolio Optimisation for the Energy Markets
Hydro-Thermal Coordination

The decision problem can be represented with the following scenario tree

Variables:
- \( \text{Vol}(i,j) = \) end volume stage \( i \), scenario \( j \)
- \( I(i,j) = \) Inflow stage \( i \), scenario \( j \)
- \( R(i,j) = \) Release stage \( i \), scenario \( j \)
- \( \text{Ci}(\text{Rel}(i,j)) = \) Thermal Cost due to release \( \text{Rel}(i,j) \)
- \( C_{ij} = \) thermal cost stage \( i \) scenario \( j \)

4 Scenarios:
1: Wet, Wet
2: Wet, Dry
3: Dry, Wet
4: Dry, Dry

<table>
<thead>
<tr>
<th>Condition</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wet1</td>
<td>P11</td>
</tr>
<tr>
<td>Dry1</td>
<td>P12</td>
</tr>
<tr>
<td>Wet2</td>
<td>P21</td>
</tr>
<tr>
<td>Dry2</td>
<td>P22</td>
</tr>
</tbody>
</table>
Scenario tree construction is based on sampling reduction techniques. The scenario aggregation in different nodes in the same stage depends on the information associated to the sample.

Scenario tree construction test example:

**Stage Number:** 1 2 3 4
**Number of Leaves:** 2 4 12 12
**Number of Periods:** 168 2184 2520 3888

**Membership Properties**
- **Global (Global)**
  - Tree Stage Count: 4
  - Tree Period Type: 2
  - Tree Stages Position: 2
  - Tree Stages Leaves: 2

**Tree Stages Positions in weeks**
- Start Week 1: t = 0
- Start Week 2: t = 168
- Start Week 15: t = 2520 + 2184 + 168
- Start Week 30: t = 2184
- Start Week 30:
  - 2 leaves
  - 4 leaves
  - 12 leaves

The uncertainty totally vanishes from week 30.
SO application in PLEXOS

- PLEXOS implements SO in LT Plan, MT Schedule, and ST Schedule for different types of decisions
  - LT Plan: Capacity Expansion Planning (SIP)
  - MT Schedule: Hydro/Gas storage management (SIP)
  - ST Schedule: Unit Commitment (SIP)
SO LT Plan

- Excellent tool for exploring the dynamics of capacity expansion and finding the key sensitivities
- Allows the use of MIP capacity expansion in systems with significant uncertainty in the incumbent generators (e.g. hydro dominated systems)
- Allows proper evaluation of expansion candidates that are subject to uncertainties in production e.g. hydro inflows, wind intensity
- Expected to favour spreading wind developments across sites to reduce energy variability
- Should make better decisions about retirement/refurbishment of existing thermal plant
SO MT Schedule

- With SO in MT Schedule PLEXOS becomes a genuine stochastic hydro model capable of modelling realistic release policies for significant storages.
- Gives better forecasts and more accurately values thermal resources inside hydro-dominated systems.
- Can model constraints that traditional DP-based stochastic models cannot; however.
- Like DP it potentially requires large amounts of memory to model a reasonable sample size.
SO in ST Schedule

- Produces more conservative (realistic) unit commitment patterns reflective of uncertainty.
- Better able to measure the impact of forecast uncertainty from wind, load, etc on the physical generation portfolio.
- When combined with the detailed transmission modelling in PLEXOS, it becomes the ultimate model for wind integration studies.
Risk Adjusted Values

Measurement Issues:

- **Deterministic Scenarios** provides a measure of value at given conditions:
  - Value of portfolio given average conditions

- **Stochastic (MCS) Simulation** measures values of all measured conditions weighted by probabilities providing the:
  - Average value of portfolio given ALL conditions

- **Stochastic (MCO) Optimization** measures values of all measured conditions weighted by probabilities providing the:
  - Optimum value of portfolio given ALL conditions

Why use Risk in Planning Decisions?

- It is likely that decisions made under deterministic planning, while optimal for the deterministic case, yield a decision which is costly under other known risks

- What is the Risk Adjusted Value?
The Perfect Foresight Problem:

- Stochastic Run is simply a deterministic (predictable) run using randomly drawn data.
- Optimization therefore assumes that you know the outcome, i.e. have perfect foresight.
- What if you need to make a decision (UC, Hydro schedule, Build/retire), based on a totally unknown future?

Stochastic Optimization

- Makes the decision, then.
- Evaluates, then.
- Runs stochastic optimizations, allowing the optimum decision to be determined.
Present Values Calculation

Additionally, in PLEXOS 7, there is the ability to calculate present values (NPV) to any desired discounting rate for any cash flow property (Revenues, Profits, Costs etc. or else any reported properties with '$' symbol in their unit field).

Net Present Value of a stream of Cash Flows:

\[ NPV = \sum_{k=1}^{\infty} CF_k \times (1 + r)^k, \text{ where } CF_k \text{ is cash flow at } k\text{-th interval, } r \text{ is a discount rate.} \]

Cash flow is reported as the amount of money that is either paid out or received, differentiated by a negative or positive sign at the end of a period. Conventionally, cash flows that are received are denoted with a positive sign (total cash has increased) and cash flows that are paid out are denoted with a negative sign (total cash has decreased).

The cash flow for a period represents the net change in money of that period. Calculating the net present value (NPV) of a stream of cash flows consists of discounting each cash flow to the present, using the Present Value Factor and the appropriate number of compounding periods, and combining these values.
Company (Portfolio) Risk

The Company class reports all required financial metrics such as e.g. Net Profit, Net Revenue et al.

Company Formulate Risk is a flag indicating if constraints should be formulated to bound Net Profit risk.

These constraints apply when running a stochastic portfolio optimization (ST Schedule Stochastic Method = "Scenario-wise Decomposition") and the simulation is multi-sample (Risk Sample Count > 1).

A constraint is then formed on each Company so that the Net Profit in each scenario is no less than Target Net Profit less the Acceptable Risk. These bounds are usually determined by first running the stochastic optimization without these risk constraints, and setting the Target Net Profit such that less desirable outcomes are constrained away.

Company Target Profit is the target Net Profit for risk constraints.

Company Acceptable Risk is the acceptable risk around Target Profit for risk constraints.
Optimum vs Best Solution

Optimum solution **does not mean** and **must not be confused** with the Best solution available ... alike

Uncertainty is not the same and is not only associated with **Risk**...
Conclusion

- With grids integrating more renewables there is a clear need to account for uncertainty in portfolio optimisation and decision making.
- Modern optimisation codes can solve two-stage and multi-stage stochastic optimisation problems with integers in both first and subsequent stages providing a robust portfolio optimisation outcome.
Thank you for your time and the opportunity

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