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Introducing Multi-Objective Decision Optimization in PLEXOS® Integrated Energy Models

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Introduction

As digital data technologies become more advanced every day and more competition arises within the Energy industry, and all other industries, it becomes fully clear that the optimization of data-based decisions is key to competing in the market. Big data gives businesses access to more information not so easily accessible in the past, nor was it ever at today's scale. However, to stay competitive, the ability to optimize data-based decisions is pivotal to running a successful business now as the nature of competition changes. In this White Paper, I define Multi-Objective Decision Optimization within PLEXOS and how advances in technologies allow for increased decision-making capability despite complex market dynamics and an increased rate of change.

Now the capacity available in PLEXOS 8.3 for conducting Multi-Objective Decision Optimization studies is fully available to the integrated Energy modelling communities of Power, Gas, Water, and renewable energy markets' users to make the most informed decisions at the most impactful times.

Complex Global Challenges and Tectonic Changes

During the last decade, strong and sometimes quite violent transitions and tectonic changes take place. Global politics are in a turmoil with multiple and major geopolitical competitions extending and unavoidably affecting global energy markets. The global energy market is in a state of flux due to strong cross-competitions between different energy sources stemming from the need to address climate change through green measures and initiatives. Complexity arises from the adoption of new

clean and sustainable energy technologies, while there are parallel tectonic changes that are taking place in science and in technologies, particularly in the areas of digital transformations.

The Opportunity of Gaining a Greater insight into Complexity

With so many new variables and vastly different time horizons in the energy investments' landscape, the cost of wrong decisions may be much higher and more difficult to recover from. From a scientific perspective, optimizing Energy Investments and Operations becomes a complex mathematical problem. Advanced Digital information technology and computing methods are required to solve problems and they are the only tools and methods to effectively support decision making and to address the increased uncertainty and complexity of this new era. Furthermore, most—if not all —modern Energy sector and related (e.g. Environmental) problems fall within the definition of Multi-Criteria Decision-Making under Uncertainty and Risk.

The ability to address all the different potential futures and objectives and what might happen in the energy markets, is more critical than ever in order to be able to meet the decision-making needs of the various shareholders that are active in the energy & related sectors. The more successful our industry can be in addressing all these potential different futures, enabling such a seamless multi objective decision optimization support as In PLEXOS, the greater the chances we have in achieving a sustainable growth, and an enhanced future prosperity and quality of life.

Analytics and Decision Optimization

When it comes to Decision Optimization, Prescriptive analytics literally represents the only set of analytical methods available that directly supports final decision making (what I can best do?) with respective actions that need to be taken.

“...If you are in a competitive marketplace—managing anything from products to people—prescriptive analytics could mean a huge boost to profit, productivity, and the bottom line. And honestly: it’s still early in the prescriptive analytics game. I’m guessing we’re only seeing the tip of the iceberg in terms of what prescriptive analytics can accomplish.”¹

Prescriptive analytics is the highest capability of analytics today that decides in improving the firms through the predictive and descriptive analytics.²

The Application of Analytics

There are three primary application areas of all analytics methods:

FIGURE 1



Simulation - This involves building models or replications of real-world business process systems to try out and test solutions before applying them, offering Descriptive, Diagnostic & Predictive analytic capabilities.

Optimization - The purpose of optimization is to achieve the best performance under the given circumstances. Optimization also involves comparing and narrowing down potential options, offering Prescriptive analytics capabilities.

Probability and Statistics - This includes using mathematical simulation and optimization algorithms and data to uncover helpful insights, uncertainties and risks, to make reliable predictions and to test possible solutions.

Decision Optimization

An IBM definition of Decision Optimization resonates well within the context of PLEXOS and complex decision support:³

People frequently use the term optimization to mean making something better. Although optimization often makes things better, it means a lot more than that: optimization means finding the most appropriate solution to a precisely defined situation. It is a sophisticated (advanced) analytics technology, also called Prescriptive Analytics, which can explore a huge range of possible scenarios before suggesting the best way to respond to a present or future situation.

The importance of finding the most appropriate solution depends on having the ability to explore a wide range of scenarios before suggesting a best response. In energy markets and environmental analytics, the ability and flexibility to apply Multi-Objective Decision Optimization methods in such a wide range of cases and variety of real-world problems, has been almost impossible before now.

Multi-Objective Decision Optimization

Multi-Objective Decision Optimization falls within the wider field of Multi-Criteria Decision Making (MCDM)⁴ under uncertainty and risk processes within an operations framework. Today, we can safely state that most, if not all, real-world decision-making processes and actions are multi-criteria (multi-objective) based decisions.

However, because it’s common does not make the process simple, and problems arise in almost all fields of policy analysis, engineering, economics, logistics etc., where optimal decisions need to be taken in the presence of trade-offs between two or more conflicting objectives.

For example:

- Developing a new component might involve the bi-objective of minimizing weight while maximizing strength
- Or in a quite typical real-world optimization problem, that of Portfolio Optimization which involves choosing an optimum investment portfolio, the bi-objective is to maximize expected returns while minimizing the risk of the portfolio. More specifically, portfolio optimization is the

1 Daniel Newman (Contributor) - Why The Future Of Data Analytics Is Prescriptive Analytics, FORBES, Jan 2, 2020.

2 S. Poornima, M. Pushpalatha, A survey on various applications of prescriptive analytics, Int. Journal of Intelligent Networks, Volume 1, 2020, Pages 76-84

3 https://datapatform.cloud.ibm.com/docs/content/DO/DOWS-Cloud_home.html

4 The term MCDM was written about in a 1979 Article called “MCDM—If Not a Roman Numeral, Then What?” by Stanley Zionts <https://doi.org/10.1287/inte.9.4.94>

process of selecting the best portfolio (asset distribution), out of the set of all portfolios being considered, according to some objective(s). The multi-objective typically comprises of maximizing factors such as expected return and minimizing costs like financial risk.⁵

Multi-Criteria Decision Making Under Uncertainty and Risk

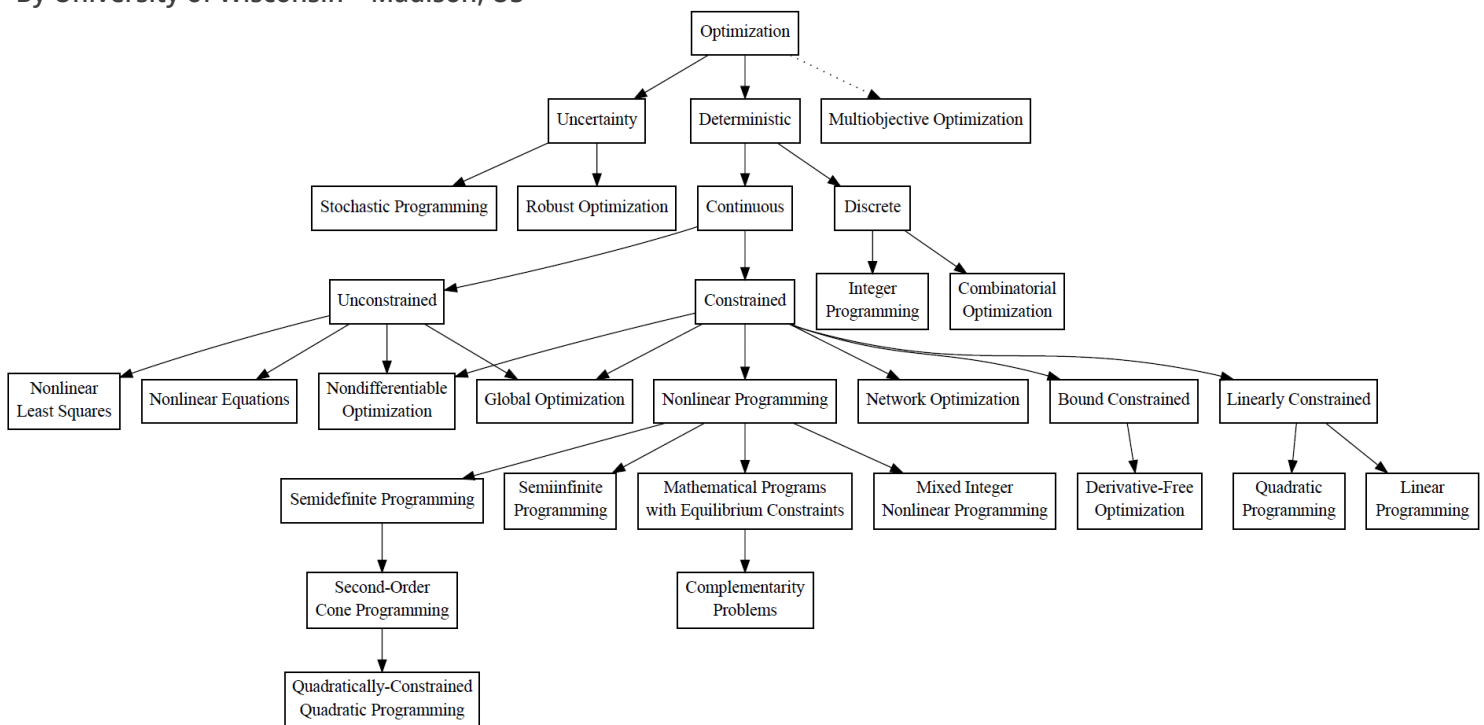
Today, these decision-making problems are practically and generally addressed by employing general purpose optimization and mathematical research tools and employing self-developed solvers and solution methods. Also, in practice, problems with multiple objectives often are reformulated as single objective optimization problems by either forming a weighted combination of the different objectives or by replacing some of the objectives with constraints. This is not the same though as the original multi-objective problem.

Multi-Objective Optimization, as an advanced optimization method, is not new. However, only recently have commercial solver developers and providers, such as IBM/Cplex and Gurobi, provided the capacity to enable software solutions to further expand into these advanced mathematical programming methods for all fields of decision optimization.

Multi-Objective Optimization v Single-Objective Optimization

The University of Wisconsin-Madison, US presents an optimization taxonomy to in which⁶, Multi-Objective Optimization is highly ranked. It stands next to the Deterministic and Uncertainty methods

FIGURE 2: OPTIMIZATION TAXONOMY
By University of Wisconsin – Madison, US



An alternate model, though, could credibly show that Multi-Objective Decision Optimization (MODO) could be positioned at the top of the optimization taxonomy and right above a Single Objective Optimization (SOO) respective box, since Single-Objective optimization can be simply seen as a limited case of Multi-Objective, with all the other branches below relevant to both of them.

⁵ A dedicated white paper about Multi-Objective Energy Portfolio Optimization with PLEXOS will be soon available also from Energy Exemplar.

⁶ <https://neos-guide.org/content/optimization-taxonomy>

In Multi-Criteria Decision Optimization, we need to formulate problems with more than one objective, since a single objective with several constraints may not adequately represent the problems faced and there is a vector of objectives that must be traded off in some way:

$$\mathbf{F}(\mathbf{x}) = [\mathbf{F1}(\mathbf{x}), \mathbf{F2}(\mathbf{x}), \dots, \mathbf{Fm}(\mathbf{x})]$$

The relative importance of these objectives is not generally known until the system's best capabilities are determined, and trade-offs between the objectives fully understood. As the number of objectives increases, trade-offs are likely to become complex and less easily quantified. The decision maker must rely on his or her intuition and ability to express preferences throughout the optimization cycle. Thus, requirements for a multi-objective design strategy must enable a natural problem formulation to be expressed and be able to solve the problem and enter preferences into a numerically tractable and realistic design problem.

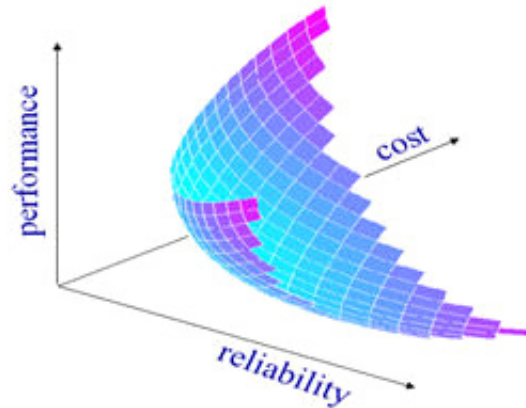
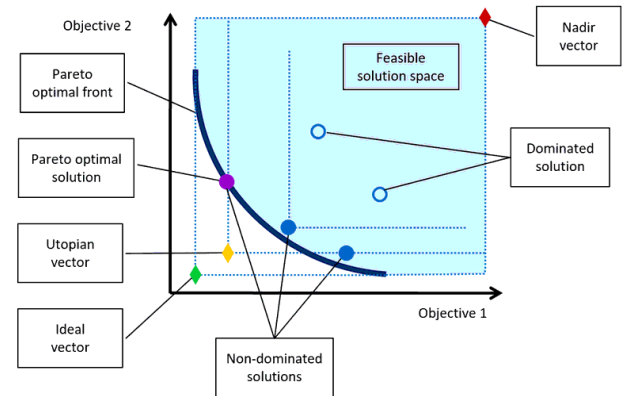
So, Multi-objective decision optimization involves minimizing or maximizing multiple objective functions (or else a vector of objectives $\mathbf{F}(\mathbf{x})$) that that can be subject to several constraints or bounds:

$$\text{MOP} : \min_{\mathbf{x} \in X} \mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_p(\mathbf{x})),$$

Because $\mathbf{F}(\mathbf{x})$ is a vector, if any of the components of $\mathbf{F}(\mathbf{x})$ are competing, there is no unique solution to this problem. Instead, the concept of noninferiority (also called Pareto

optimality), must be used to characterize the objectives. A Pareto optimal solution refers to a set of solutions, around which there is no way of improving any objective without degrading at least one other objective or else an improvement in one objective requires a degradation of another (a non-inferior set of solutions). The set of Pareto optimal outcomes is often called the Pareto front, Pareto frontier, or Pareto boundary.

FIGURE 3 - BI-OBJECTIVE⁷ & TRI-OBJECTIVE⁸ OPTIMIZATION PARETO FRONTIERS



The Bi-objective Pareto frontier example shows the set of Pareto optimal solutions (those that are not dominated by any other feasible solutions) for a problem. The shaded area represents the area of potential feasible solutions' and those pareto optimal front solutions that are closer (with the lower Euclidean distance) to the ideal vector point are the preferred multi-objective solutions. The same Minimum Euclidean distance measure also applies in the tri-objective or any other multi-objective case optimum solutions.

Some example problems include analysing design trade-offs, selecting optimal product or process designs, or any



⁷ Maria Siurana Paola - Modelling and Multi objective optimisation for simulation of cyanobacterial metabolism, PhD Dissertation, Universitat Politècnica de Valencia, 2017.

⁸ https://www.sheffield.ac.uk/acse/people/peter_fleming/introme

other application where you need an optimal solution with trade-offs between two or more conflicting objectives.

Lexicographic (Sequential) vs. Blended Multi-Objective Optimization

Optimization problems with multiple linear objective functions can be solved by employing modern commercial solvers (e.g., CPLEX in PLEXOS) that offer a mixture of blended and lexicographic or hierarchical optimization.

A lexicographic objective supposes that a priority order has been given among the various objective functions. This order allows you to define a lexicographic order among solutions. A solution is lexicographically smaller than another one if, in the first objective where they differ (following the order), it is smaller. An optimal solution is then one that is lexicographically minimal (or maximal depending on the optimization sense⁹).

A blended objective consists of simply the linear combination of several objectives with given weights. PLEXOS with CPLEX solver can combine and handle both blended and lexicographic objectives in the same optimization problem. Both weight and priority are always specified for each objective. This seamlessly combines the blended and hierarchical approaches.

To understand how this works, more detail is needed on how hierarchical objectives are handled. When someone specifies a different priority for each of the objectives, the solver performs separate optimization steps. In each step, in decreasing priority order, it optimizes for the current objective, multiplied by its Objective Weight attribute, while imposing constraints ensuring that the quality of higher-priority objectives isn't degraded by more than some specified tolerances (an either Absolute Tolerance or a Relative (%) Tolerance value).

PLEXOS Case Study: Multi-Objective Decision Optimization in PLEXOS Power Generation Unit Commitment and Dispatch Modelling

PLEXOS has been demonstrated as a real-time dispatch or ex-ante or ex-post market-clearing engine e.g., to audit the operation of other market-clearing engines and simulation software. Now PLEXOS has demonstrated the ability to do Multi-Objective Decision Optimization.



A multi objective function allows the user to specify additional objectives, beyond the usual profit maximization or cost minimization in the classical Unit Commitment/ Energy Dispatch (UC/ED) problem. The newly developed PLEXOS multi-objective optimization capability was employed and demonstrated in a Great Britain and surrounding countries PLEXOS study model, in a variety of UC/ED cases that multi-objective decision optimization can be applied, bringing significant added value to PLEXOS users globally. The extent and variety of cases in the UC/ED field of applications is already enormous.

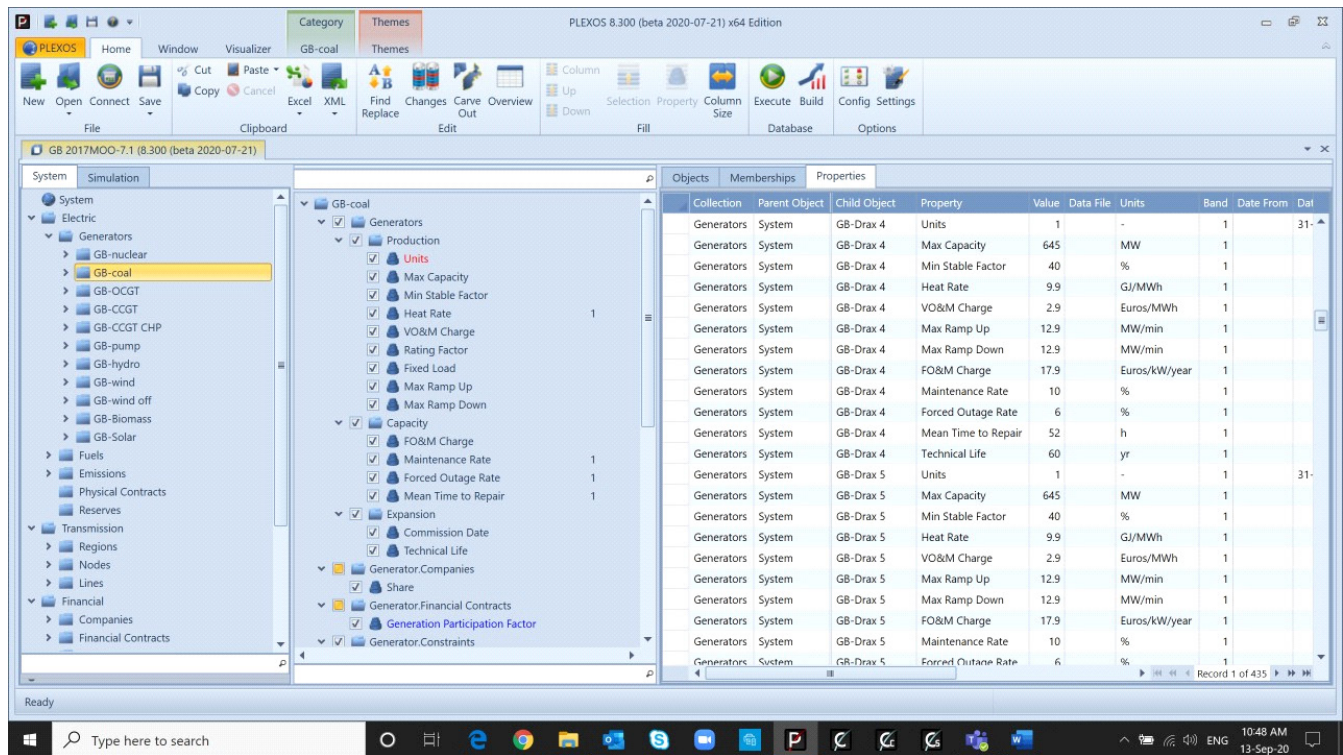
Firstly, the single objective of maximizing the profits of a company's generation assets portfolio was demonstrated along with the company's unit commitment and the respective energy dispatch of its generators. This is usually set up in PLEXOS as a Price (input) Based Unit Commitment and Dispatch plan problem, with forward electricity market price curves as an input. This then compared against several respective multi-objective UC/ED plan scenarios.

A first test was conducted against historical (known) price outcomes to try to re-optimize the unit commitment and dispatch plan of a generation company with a substantial portfolio of coal and other thermal generation assets (OCGTs, CCGTs & other). Its significant emissions costs were considered in order to maximize its net portfolio profits, in a PLEXOS demo GB2016 electricity market model.¹⁰ The model compared typical single (max profit) objective models' resulted generators' dispatching plans against various multi-respective objective models' solutions plans, that have revealed the strength and enormous value of the later, obtaining also several associated Pareto frontiers.

⁹ https://www.ibm.com/support/knowledgecenter/en/SSSA5P_12.9.0/ilog.odms.studio.help/CPLEX/ReleaseNotes/topics/releasenotes1290/newMultiObjOptimization.html

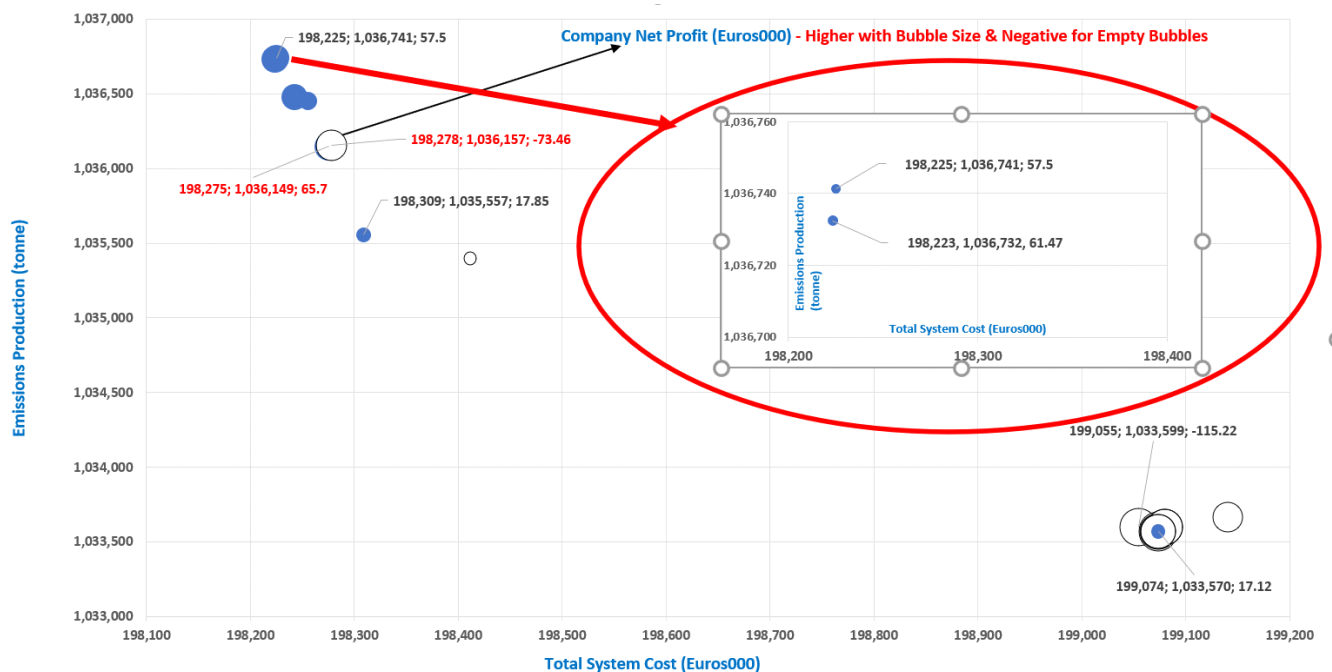
¹⁰ The GB2016 electricity market model as an interesting study year since a significant market price volatility was observed during the last months of this year post Brexit vote

FIGURE 4: PLEXOS GB MARKET CASE STUDY MODEL OF MULTI-OBJECTIVE OPTIMIZATION



In this example, specifying a secondary objective of minimizing the total system's costs in addition to a third objective of minimizing the company's total generated emissions, a 3D Pareto frontier was obtained which has been projected and shown in the 2D figure below.

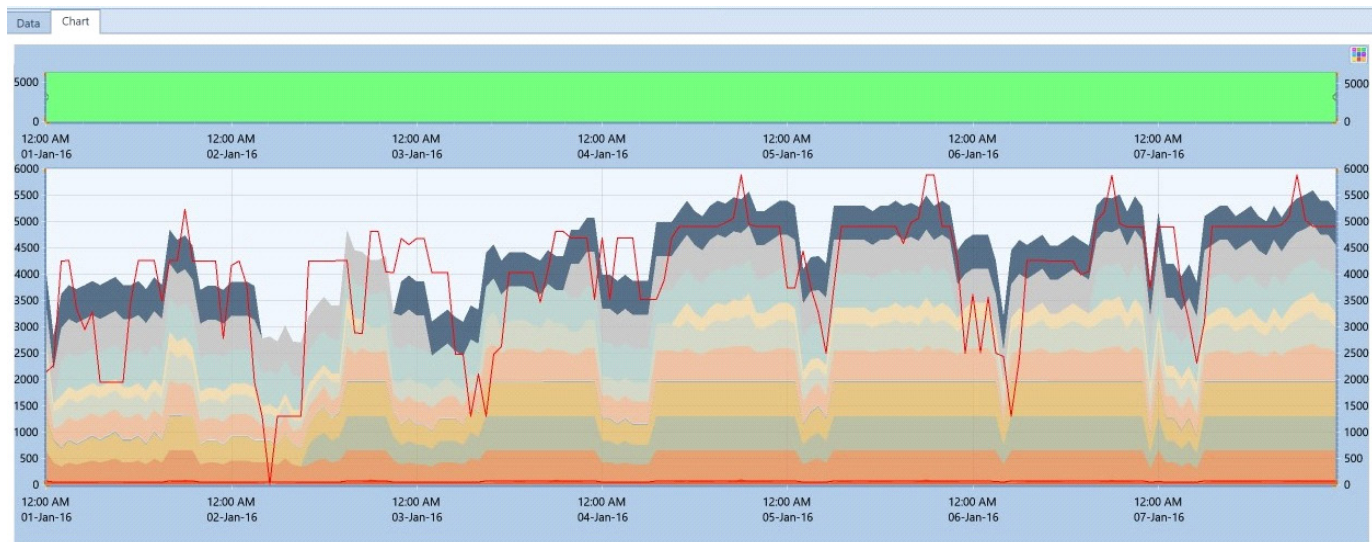
FIGURE 5: 3D MULTI-OBJECTIVE OPTIMIZATION PARETO FRONTIER OF GB GENERATION COMPANY PORTFOLIO, "HEAVY" ON THERMAL GENERATION ASSETS.



Note that the bubbles' size and filled or empty bubbles representing respective higher/lower generation portfolio profits or losses. Remarkably, even for such a coal heavy generation portfolio, there are still several profitable Pareto frontier points as seen in the higher left corner of the graph. While emissions are higher, total system costs are lower. Additionally, the low right corner of the graph shows where emissions production is lower and total system costs are not significantly higher.

The following graph shows another case, with the resulted unit commitment and dispatch plan of the above company's generation portfolio. All company's plants dispatching (total generation stuck) are shown for 1 week. The multi-objective (max profit/min system cost) detail per plant dispatching results are compared to the resulted total dispatch of the same power plants by a single-objective (max profit) run, the later shown with the red line.

FIGURE 6: MULTI-OBJECTIVE V SINGLE-OBJECTIVE OPTIMUM DISPATCH PLAN OF COMPANY'S GENERATION PORTFOLIO



In figure 7 the orange line represents the Company' portfolio (Generation) Net profits results from the above multi-objective decision optimisation of dispatching plan, while the blue line those profits that would have been resulted from the respective single profit maximisation objective dispatching plan.

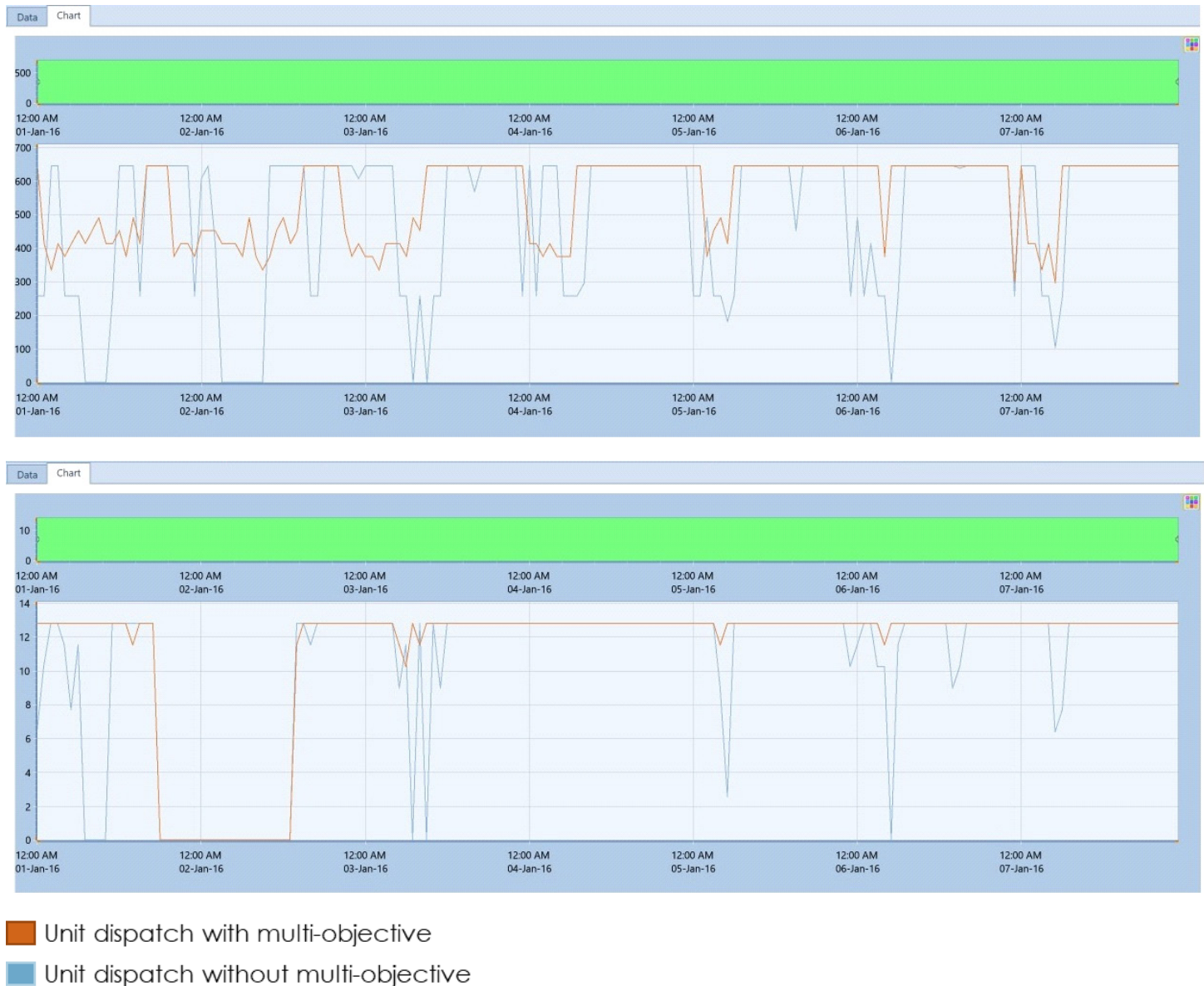
FIGURE 7 MULTI-OBJECTIVE V SINGLE-OBJECTIVE NET PROFITS OF COMPANY'S GENERATION PORTFOLIO



In both figures 6 & 7 it is clearly shown that both the resulted Company's total generation/energy dispatching as well as, its net profits were much higher in the multi-objective optimisation case.

In another example, we specify a secondary objective of minimizing company's generators ramping, examining all similar economically optimal solutions, and chose the solution which minimized the ramping of units, essentially smoothing out the dispatch profile to something which can be used operationally. The following two (2) graphs show two output schedules for two units of the portfolio.

FIGURE 8: MULTI-OBJECTIVE V SINGLE-OBJECTIVE OPTIMUM DISPATCH PLAN OF TWO COMPANY'S GENERATORS



Both single and multi-objective outputs are from the same model/problem and resulted in the same total revenue however, the spikey nature of the dispatch of the plants was smoothed out over all units in the portfolio's multi-objective decision optimization case.



Conclusion

In the Era of Complexity and Big Data, Energy Companies try to harness analytics technologies to predict trends and prescribe the proper course of action to achieve their core objectives. Information (data) just for information, or else information that cannot be transformed into valuable knowledge and subsequent actions, it is merely useless.

Predictive analytics answers what may happen, while prescriptive analytics and in particular, Multi-Objective Decision Optimization is the only method available that can lead to specific actions, providing feasible and optimum answers to multiple what-if scenarios and taking into account various objectives' trade-offs and potential futures. PLEXOS successfully provides for many years now Predictive Analytics (Scenario Analysis, MC Simulations and

Stochastic Optimization) capacity where in combination with the new Multi-Objective Decision Optimization functionality can yield maximum benefits at the enterprise level.

As Grant Thornton have already quoted in a public report: "Next analytics revolution is the ability to couple predictive technologies with prescriptive technologies..."¹¹

And Energy Exemplar, as a pioneer in both Energy Predictive and Prescriptive analytics, with its New PLEXOS Multi-Objective Decision Optimization functionality brings this next Energy Analytics revolution today.

www.energyexemplar.com | info@energyexemplar.com

¹¹ Predictive and prescriptive analytics: Transform the finance function with ground-breaking decision support, Grant Thornton, FERF.

