

Visual MESA Energy Management System

Forecasting and Data Management Tools For Utilities Assets Scheduling

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A rokogawa Company

- Introduction
- Technology Overview
- Case Study
- Summary

Agenda

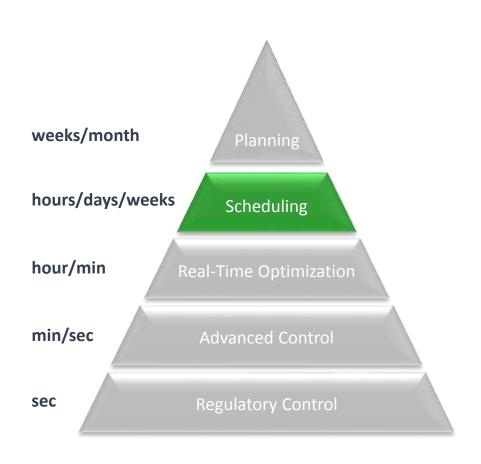


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- Technology Overview
- Case Study
- Summary

Agenda

Optimal Scheduling in District Energy Systems





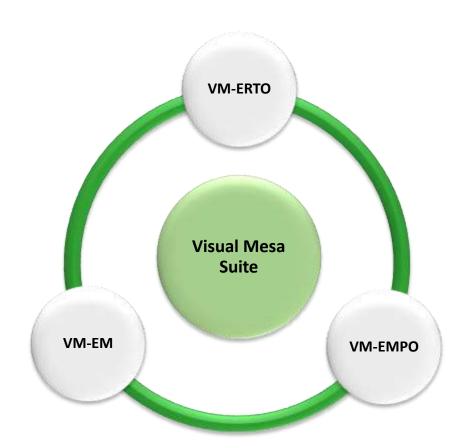
The decision making process in the operation of district energy systems is usually composed of different levels:

- The regulatory/advanced control level allows the automatic adjustment of key variables at a high frequency (seconds/minutes).
- The **real time optimization** level defines the optimal set points of the system considering the current conditions and assuming steady state. Usually every hour or fifteen minutes.
- The **scheduling** level defines the operation of the system in a short-term time horizon (i.e. hours/days) based on predicted conditions.
- The **planning** level is usually used to take long term decisions (e.g. system retrofit).

The Visual MESA Energy Management suite provides recommendations at different levels, in particular at the scheduling level via the VM-EMPO

Visual Mesa Energy Management Suite





Systems exposed to minimum up or down times, start-up and shut-down costs, spinning reserves, fuel storage, thermal energy storage, electricity price variability are typical cases handled by VM-EMPO

VM-ERTO

Visual MESA Real Time Optimizer is the leading real-time solution for modeling and optimization of energy systems

VM-EM

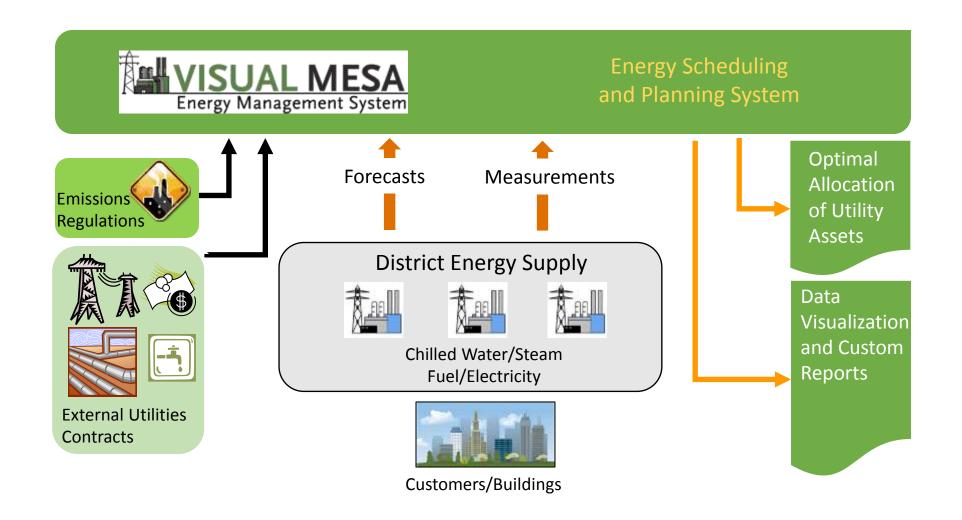
Visual MESA Energy Monitor offers a feature set specifically built for the monitoring of energy systems (KPI Calculation, etc)

VM-EMPO

Visual MESA Multi-Period Optimizer is the energy management tool for the optimal planning and scheduling of utility assets.

VM-EMPO Architecture

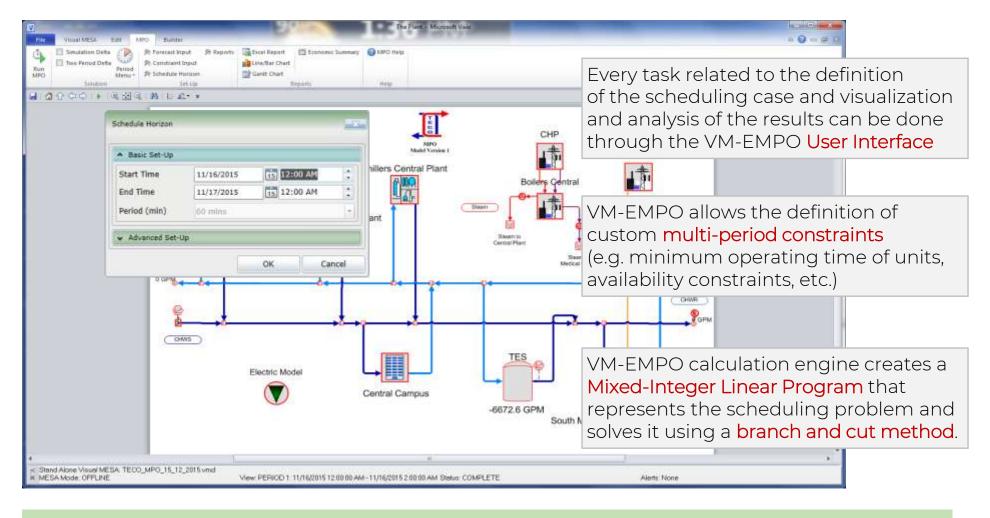




Optimal Planning and Scheduling of Utility Assets, Juan Ruiz and Oscar Santollani, IETC 2016 Proceedings

VM-EMPO User Interface





VM-EMPO has **recently** introduced a set of **data management tools** to allow the **forecasting** of key variables.

Multi-Period Optimization of District Energy Supply, Development of Day-Ahead Scheduling to Supplement Real-Time Optimization at TECO, J. Garcia, J. Ruiz, T. Reitmeier, International District Energy Association (IDEA) Annual Conference, Miami, USA, June 2013

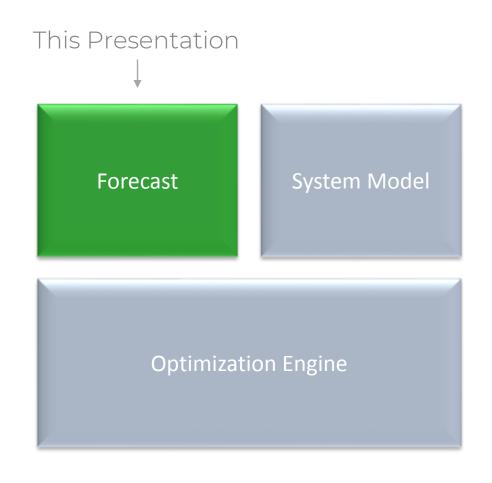


- Agenda

- Introduction
- Technology Overview
- Case Study
- Summary

Scheduling System Components



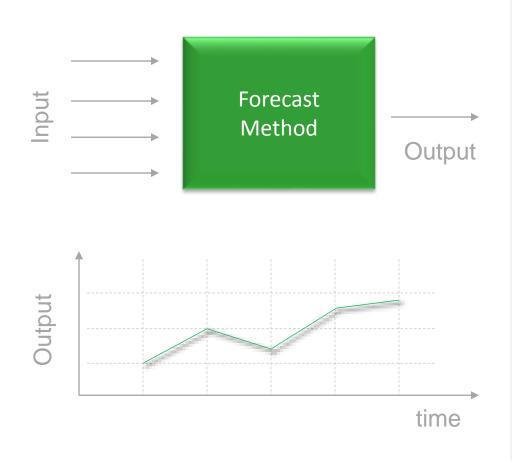


Scheduling systems are composed with at least the following elements:

- System Model: It represents the physical behavior of the system under different operating conditions.
- Optimization Engine: Based on the predicted behaviour of the system and the operating constraints it finds the optimal operating conditions.
- Forecast: It provides a prediction of key variables that directly impact the operation of the system.

Forecasting in District Energy Systems





In order to find the optimal operating schedule of a system, the forecast of key variables, such as chilled water demand, electricity prices, ambient temperatures need to be obtained.

Forecasting the values of key variables requires at least two main elements:

- Data Inputs from where a given output can be inferred.
- Forecast method that will generate the prediction of a given output by manipulating a set of inputs.

Data Sources for Forecast Generation





Relational Databases are usually used to store production plans, equipment availability, etc.



A plethora of **RESTful services** are available that provide useful information. For example, weather forecasts can be accessed via this service.



Excel files are frequently encountered within the logistics and operation tools. More often than not, they are valuable source of information.



Real-time databases are used to track the history of key variables. This history can be exploited to generate better forecasts.



There are many **applications** that are frequently used to simulate **complex systems** in the district energy plants. Accessing this information may be very useful in the prediction process.

Data Analytic Tools





Stand-alone applications such as R, SAS, etc. can be used to develop inferential models. They provide a large library of different statistical algorithms and data handling techniques.

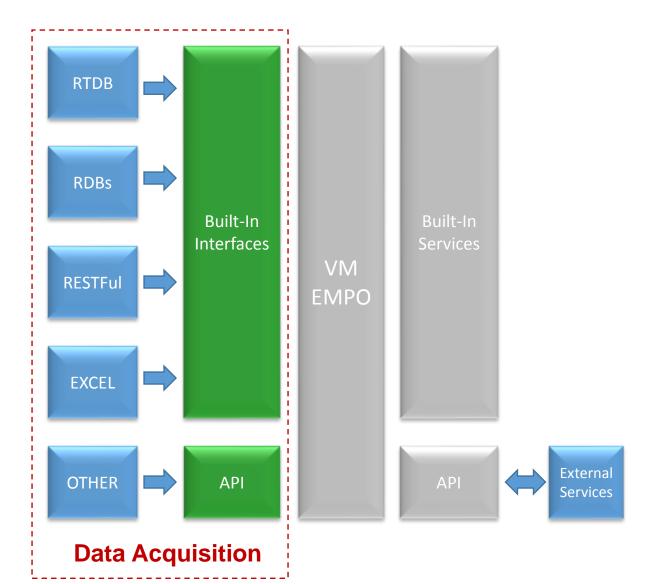


Many analytic tools are available also as **cloud services** (e.g. Google Analytics). Users only need an internet connection to access them.

VM-EMPO provides connectivity to different data sources and data analytic tools.

VM-EMPO Data Management





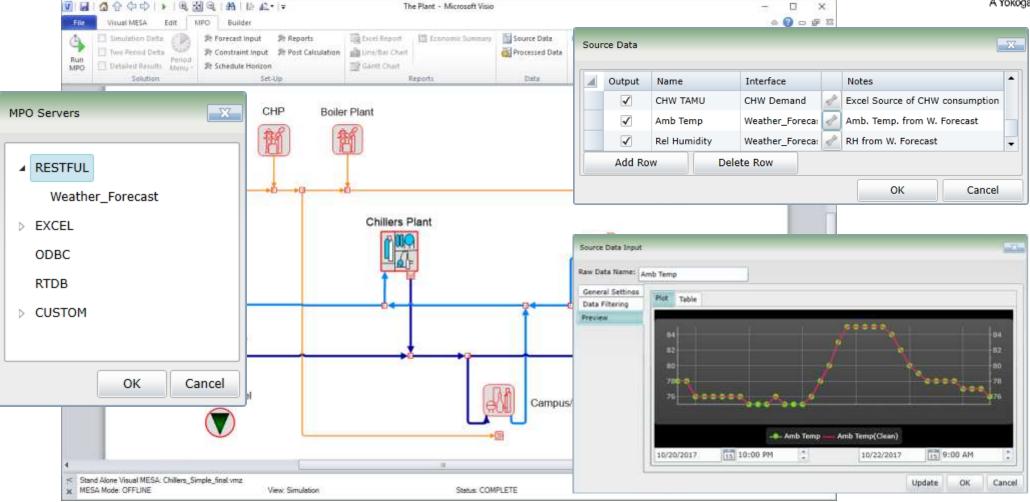
VM-EMPO has a set of features that enhances its original data acquisition capabilities.

- VM-EMPO can connect to virtually any data source.
- It provides built in interfaces for the most common data sources (RTDB, RESTful, Excel, etc.).
- It provides an API to connect to custom sources.

All data sources can be configured via the typical VM-EMPO user interface

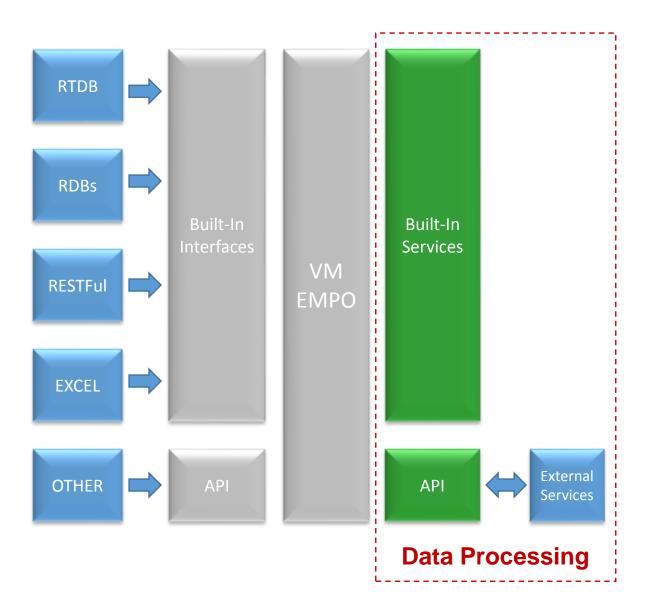
VM-EMPO Data Management User Interface: Source Definition





VM-EMPO Data Management



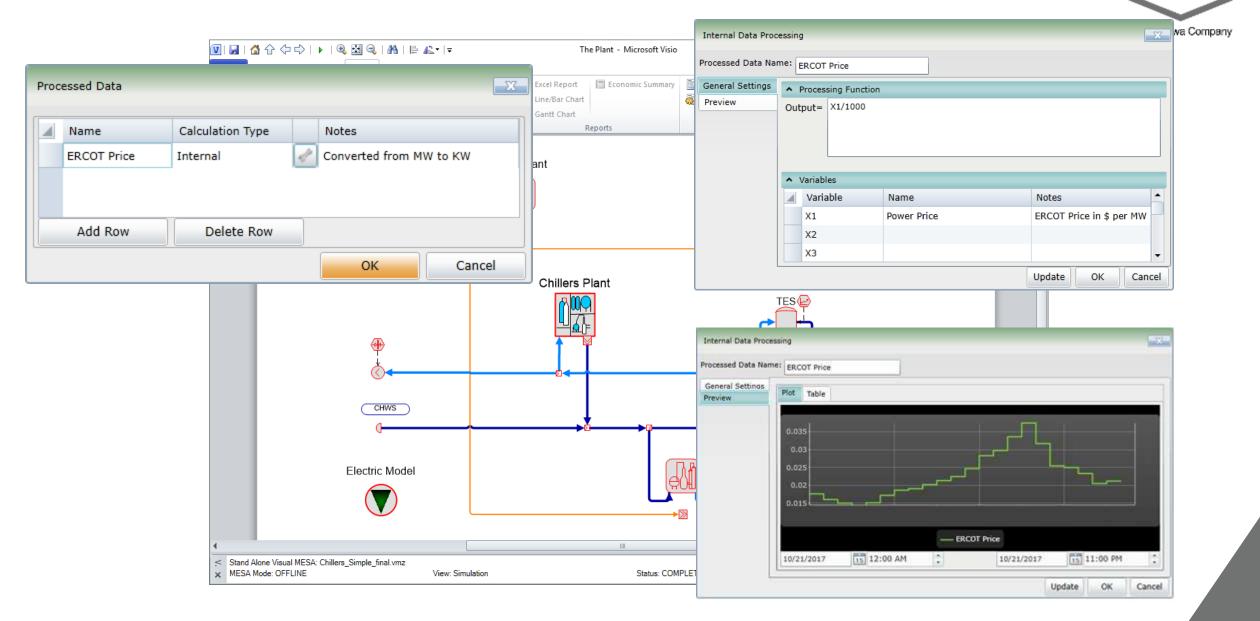


VM-EMPO has added a set of features that enhances its data processing capabilities

- VM-EMPO provides built-in services to process data series.
- It provides an API to use external services (e.g. cloud services).

The connectivity to the different data analytic tools can be configured via the typical VM-EMPO user interface

VM-EMPO Data Management User Interface: Processed Data Definition





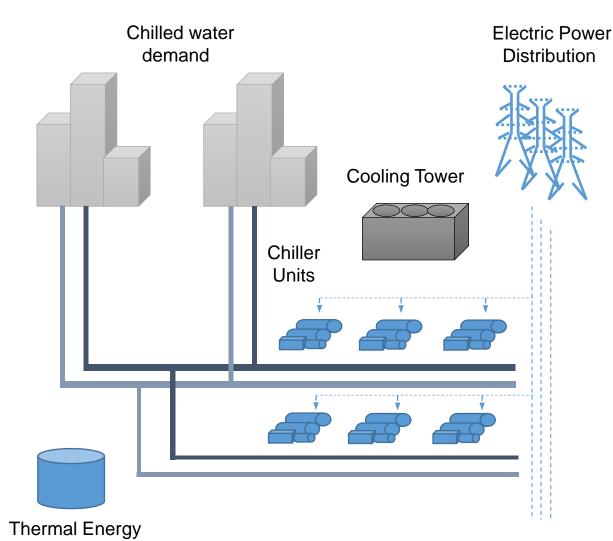
- Technology Overview
- Case Study
- Summary



Agenda

Forecasting in Short-Term Scheduling of District Cooling System





Storage

VM-EMPO was applied to find the optimal short-term schedule of a typical district cooling system.

- The main goal of most district cooling systems is to centrally produce and distribute chilled water at a minimum cost while satisfying demand.
- Chillers are the main components of the chilled water production plants. The production cost of chilled water plants that use electric powered chillers is deeply sensitive to electricity price variability.
- To minimize the production cost, thermal energy storages are often used.

To find the optimal schedule, a **forecast of key variables needs to be developed**. This is seamlessly integrated in VM-EMPO.

Forecasted Variables



In general, selecting the required variables to be forecasted depends on the problem at hand. Engineering knowledge of the system as well experience on model limitations plays an important role in this process.

Electricity Price

Since the main energy source of this system is electric power, predicting its day-ahead price is Important to clearly define the expected costs.

Chilled Water Demand

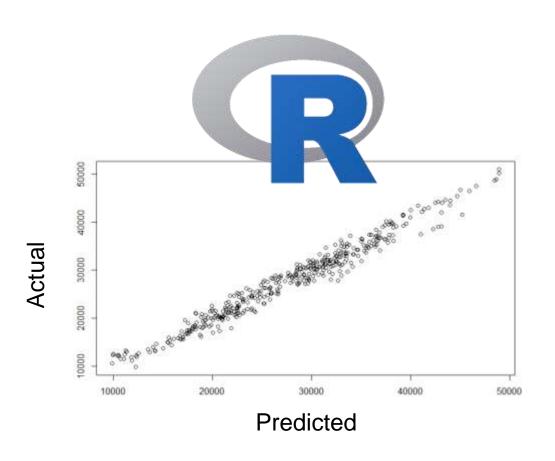
The main product of the cooling systems is given by the chilled water. Predicting the demand is very important as it has a direct impact on equipment allocations

Cooling Tower Return Temperature

Cooling tower return temperature impacts the chiller efficiency, which ultimately affects its operating cost.

Chilled Water Demand Forecast





The analytical tool R was used to predict the hourly chilled water demand.

- It was found that the **inputs** that have the most impact on the prediction are:
 - Ambient Temperature
 - Relative Humidity
 - Time of Day
 - Season
- The predictive model that led to the minimal prediction error was a neural network (MONMLP).
- The model predictions are available ondemand through the VM-EMPO external interface.

Electric Power Cost Forecast





The electricity price forecast was obtained from the ERCOT server*.

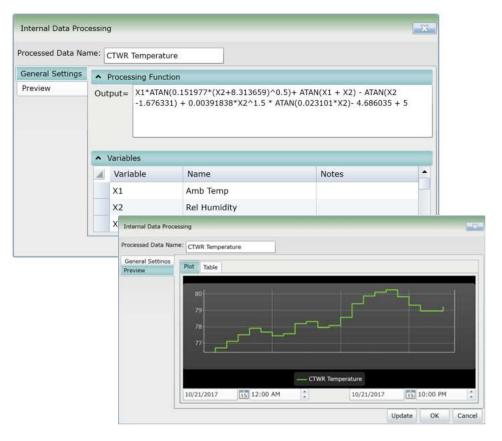
- The Electric Reliability Council of Texas (ERCOT) manages the flow of electric power to 24 million Texas customers representing about 90 percent of the state's electric load.
- ERCOT provides day-ahead market price forecasts for different hubs as well as real-time price information.
- Through the set of available interfaces,
 VM-EMPO can access these forecasts on demand.

^{*} ERCOT website address: http://www.ercot.com

Cooling Tower Water Return Temperature Forecast







The cooling tower water return (CTWR) temperature was correlated using the **built** in feature in VM-EMPO.

- CTWR temperature is directly related to the wet bulb temperature.
- The wet bulb temperature can be estimated* from the dry bulb temperature (i.e. ambient temperature) and relative humidity.
- By using Stull's correlation and updated input values, VM-EMPO predicts the CTWR temperature at each optimization run.

^{*} Stull, R. (2011), Wet-Bulb Temperature from Relative Humidity and Air Temperature, J. Appl. Meteor. Climatol., 50, 2267–2269

Summary of Forecasted Variables



Inputs	Output	Forecast Method	Data Processing Technology
Ambient Temperature Relative Humidity Time of Day Season	Chilled Water Demand	Neural Network (MONMLP)	R Package
Ambient Temperature Relative Humidity	CTWR Temperature	Stull's Correlation	VM-EMPO Built-In Feature
Day-Ahead Electricity Price	Day-Ahead Electricity Price	Proprietary Algorithm (ERCOT)	ERCOT Service

Remarks:

- Each input was accessed via the data acquisition capabilities of the VM-EMPO.
- The ambient temperature and relative humidity have been obtained from the weather forecast provider via the VM-EMPO RESTful interface.
- The day-ahead electricity price was acquired via the ERCOT service through a VM-EMPO Custom interface.



- Technology Overview
- Case Study
- Summary



Agenda

Summary



- Scheduling tools for the optimal operation of district energy systems rely on the forecasting of key variables (e.g. electricity prices, chilled water demand, etc.)
- The forecasting of key variables depends on a set of data inputs which can be found in different sources (e.g. RTDBs, RESTful services, etc.)
- The **relationship** between **input data** and the **required forecasts** can be complex, often requiring to develop detailed **predictive models**.
- Many data analytic tools are available (i.e. stand alone, cloud services), which allows the user to select appropriate predictive models.

VM-EMPO provides the user with the necessary data management tools to acquire, process data and ultimately generate forecasts that are used to obtain the optimal operating schedule in district energy systems.

Acknowledgments: We want to thank TECO for being one of the main motivations behind this study.