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A Decision-Guided Energy Management Framework for Sustainable Manufacturing

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ABSTRACT

A growing number of manufacturing industries are initiating efforts to address sustainability issues. According to the National Association of Manufacturers, the manufacturing sector currently accounts for about one third of all energy consumed in the United States [1]. Reducing energy costs and pollution emissions involves many areas within an industrial facility. Peak electric demands are a significant component in the cost of electricity. Electric demand management relates to electric tariff rates, new power generation, and incentives to curtail peak usages. Shifting some equipment/machine usage to the periods of lower cost or using stand-by local generators during the peak demand period can yield important savings. Analysis of these options is important to decision makers to avoid unnecessary high cost of energy and equipment. This paper proposes a Decision-Guided energy management in manufacturing (DG-EMM) framework to perform what-if analysis and make optimal actionable recommendations for a manufacturing facility both on (1) operational energy management including load shedding, curtailment, and local generation and (2) planning and investment decisions for introducing renewable technologies. The DG-EMM is based on the novel technology of the Decision-Guidance Query Language (DGQL), which is a tool for fast development and iterative extension of decision-guidance and optimization solutions. The proposed DG-EMM will support user-defined objectives for optimal recommendations, such as minimizing emissions and energy costs and maximizing Return on Investment (ROI). A case study of the peak demand control for an example manufacturing facility is discussed.

INTRODUCTION

More and more manufacturing industries are examining how to make their operations more sustainable. Sustainability related issues, such as energy consumption, emissions, and other environmental impact, are becoming a more integrated part of operational and long-term planning decisions in manufacturing. The Organization for Economic Co-operation and Development (OECD) states that *Sustainable Manufacturing will reduce the intensity of materials use, energy consumption, emissions, and the creation of unwanted by-products while maintaining, or improving, the value of products to society and to organizations*. The report further expands on the statement *the infrastructure that enables it. Resource consumption is one of the largest factors affecting profitability and competitiveness. Material, labor and maintenance costs can be difficult to reduce without upsetting the delicate balance between product quality and process reliability. However, reducing energy costs and improving energy efficiency in production processes is easier than one may think.* [2]

Manufacturers have always needed energy to keep factories open and production lines running, but energy management has had a lower priority compared to that of meeting production requirements. Energy was simply a cost of doing business, a line on the corporate balance sheet. The U.S. Energy Information Administration (EIA) expects substantial increases in energy prices over the next two decades. "*then manufacturers, who don't have much leeway when it comes to raising prices on their goods, will have to learn to run factories on less energy or risk financial strain.* [3]"

Improving energy efficiency, saving energy costs, and reducing emissions are plant-wide activities. Many manufacturers have made efforts in making their operations more energy-efficient in recent years. They have replaced energy-intensive equipment and initiated preventive maintenance programs to ensure that factory machinery is in optimal running condition. Companies such as Boeing, Ford, Fujitsu, General Motors (GM), Honda, and Philips have set goals for reducing energy usage, CO_2 emissions, and water usage, limiting waste, and promoting recycle [4]. For example, Fujitsu has used energy-saving equipment, revised manufacturing processes, adjusted lighting and air conditioning, used simulations to model energy usage, and used renewable power [5]. GM is implementing an aggressive program employing EPA's ENERGY STAR practices to reduce energy usage across its global facilities. From 1995 to 2004, GM reduced its North American facility energy footprint by 26.6 percent. As a charter Partner in EPA's Climate Leaders program, GM committed to a 10 percent reduction in CO_2 emissions from 2000 to 2005 for its North American facilities [6]. SAIC has used its Energy Management System (EMS) to realize significant facility efficiencies and cost savings for some large auto manufacturers in the U.S. EMS helped monitor and control nearly 20 million square feet of facility with millions of dollars in savings [7]. Mort [8] has proposed several low-cost practical projects: 1) Metering, 2) Demand Control, 3) Heating, Ventilating, and Air Conditioning (HVAC) optimization, 4) Compressed Air, 5) Lighting, and 6) Heat Recovery. He stated that combining these projects provides savings exceeding 10% of the annual energy spent with an average payback of less than one year for a company. A standby/local generation facility reduced Boeing Helicopters' utility cost by several million dollars per year for a period of seven and one-half years [9].

These examples show that the manufacturing industry has made progress with sustainability projects and energy management. However, most of them are stand-alone projects. The solutions are provided on a problem by problem basis, without a systematically structured and generalized reusable approach. Many of the complex interactions were not taken into account and could not be handled. Some companies provide demand controllers, which are programmed with a set of rules to monitor and control the actual energy usage and determine which equipment can be shut down or slowed down and for how long [10]. However, these static rules are not sufficient to satisfy the dynamic energy management needs (peak demand, utility rate schedules, dynamic pricing, peak demand pricing, time-of-day usage, load shedding, local generation, spot market, renewable resources, real time scheduling and control of loads). Also, many of their solutions are hardcoded and not extensible. Only those manufacturers that plan to manage energy efficiency and emissions in a systematic, dynamic, consistent, quantitative, and optimal manner will have a competitive advantage going forward, but they need methodologies and tools to achieve this higher-level energy management.

Decision optimization is an effective tool to make the best decision out of a multitude of possible alternatives by means of rigorous mathematical techniques. A typical optimization model used in operations research (OR) specifies (1) decision variables, (2) constraints that have to be satisfied, and (3) an objective function to be optimized. A feasible solution to an OR model is an instantiation of values from corresponding domains to decision variables that satisfies all the constraints. An optimal solution is a feasible solution that makes the objective minimal or maximal, as required, among all feasible solutions. Modeling of an industrial process using A Mathematical Programming Language (AMPL) presents a considerable challenge due to the complexity. Brodsky et al. [11] [12] proposed a Decision Guidance Management System (DGMS) data model that is an extension of the relational model with probability distributions over a set of attributes as random variables. DGMS supports functions such as what-if analyses, monitoring and control, statistical learning, and decision optimization using the Decision Guidance Query Language (DGQL), which is an extension of Structured Query Language (SQL). The DGQL is simple and intuitive for database application developers or business personnel with database skills. The DGMS greatly simplified the efforts for both developer and users for decision optimization. The framework proposed in the next section is based on this DGMS technology.

The contributions of this paper are:

1. Development of a generic framework that provides analysis of action options for energy management and recommendations for both operational and investment planning for sustainable manufacturing.
2. Requirement analysis for demand control DGQL modeling for energy efficiency manufacturing.
3. Demonstration of the proposed methodology using a case study of DGQL model of energy demand control.

The paper is subdivided into five main sections. The next section introduces the proposed Decision-guided energy management in manufacturing (DG-EMM) framework, followed by discussion on requirement analysis of DGQL modeling for demand control in manufacturing, and then a case study of DGQL model of demand control for a manufacturing plant is discussed. Finally, a summary is provided and future work is discussed.

DECISION-GUIDED ENERGY MANAGEMENT IN MANUFACTURING FRAMEWORK

The Decision-guided energy management in manufacturing (DG-EMM) framework is proposed for both enterprise energy management and sustainability investment and planning within industrial facilities to support production schedule, facility load control, utility and curtailment contracts, clean energy resources, on-site storage, and local generation [13]. Figure 1 shows the framework of DG-EMM, which consists of a DGMS that is built on a relational database management system (R-DBMS). It is also designed as an extensible technology platform on which other applications can be constructed. The DG-EMM framework is an open, flexible information technology architecture in which existing production systems and EMS can be integrated with database-driven optimization modeling capabilities. Other description models (e.g. system dynamics model; discrete event simulation model) can also be integrated into the proposed framework to aid decision making. A detailed description of each block in the DG-EMM diagram will be discussed in the following subsections.

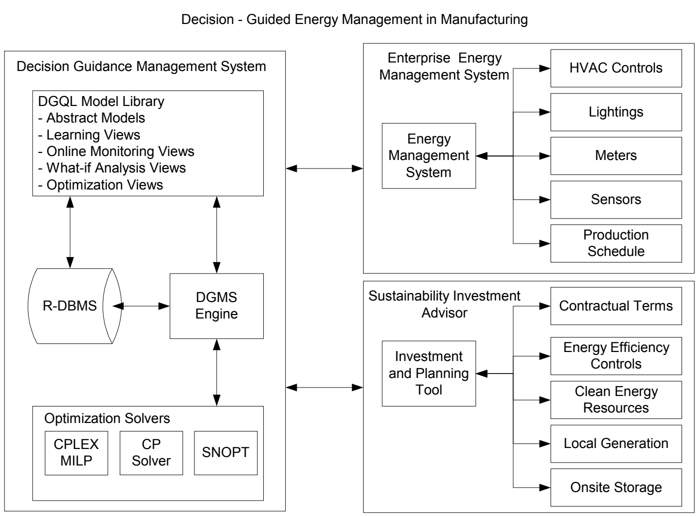


Figure 1. Decision-guided energy management in manufacturing

Decision Guidance Management System and DGQL

The DGMS platform allows for the fast iterative development of decision-guidance systems. DGMS supports 1) the integration of the data acquisition and construction of learning sets, 2) learning from the learning sets, using parameterized transformers and optionally defining an estimation utility, such as minimizing the sum of squares of errors, 3) probabilistic prediction and simulation using expressions that involve random variables, such as expectation, variance and probability of a logical formula, and 4) formulating and solving stochastic or deterministic optimization, where search space is defined as a set of feasible non-deterministic query evaluations. The domain knowledge for all these tasks is expressed in DGQL, so that the development of models is as simple as the development of database reporting applications.

The four major functions DGMS supports do not need to be manually formulated when analyzing sustainable manufacturing energy management applications in an industry facility. Rather, they are automatically derived from abstract model views by the DGMS compiler to describe each application component, and factors such as manufacturing processes, production schedules, equipment/machine, energy efficiency, emissions control, waste control, sensing and communication, and contractual terms for procurement of electricity. Other scenarios ranging from loads priority, local generation, onsite storage, and renewable energy resources to the charging of the Plug-in Hybrid Electric Vehicle (PHEV) and Electric Vehicle (EV) can be represented with such database views. Essentially, each such model is comprised of table schemas that hold the relevant information and SQL views that compute their business metrics, such as energy consumption, emissions, and operational costs. They can also be annotated by indicating that some of the table columns are unknown, while another view can be annotated to indicate that the value it computes (e.g., adjusted cost) is to be used as an optimization objective. Given this information, The DGMS engine automatically generates, at run time, the corresponding formal mathematical problem with mathematical equations, inequalities, and the objective function and deploys a mix of algorithms best suited for the problem at hand, e.g., a Mixed Integer Linear Programming (MILP) using IBM ILOG CPLEX optimization solver. Therefore, when a new component is introduced, the only requirement is to simply add an SQL view model for this component, whereas all the DGMS functions are automatically implemented with the use of the DGMS compiler.

The DGQL model predicts the minimum amount of energy needed to meet production requirements, with the least amount of emissions, at the lowest possible cost, and maintains the comfort level for employees. DGQL's "what-if" forecasting scenarios can help facility managers optimize production and facility energy performance by analyzing the actions, costs, impacts, savings, payback period, and Return on Investment (ROI) of multiple strategies for different energy efficiency options. It removes guesswork and helps users to discover which efficiency opportunities offer the quickest or highest payback potential. With the appropriate abstract model views, the DGMS will support decision optimization functions such as [14]:

- Optimal operational scheduling, including production, local generation, spot market purchase, on-site storage charge, and PHEV and EV charging
- Optimal EMS thermostat settings
- Optimal contractual terms including curtailment level commitment and peak demand limits
- Optimal payback period and ROI for renewable resources, energy storage, and local generation

Enterprise Energy Management System

In addition to the energy needs like those for a facility such as a university campus or large government building, most industry facilities have energy intensive manufacturing processes. Managing energy consumption in industry facilities will reduce operating costs in this increasingly competitive global marketplace.

Manufacturing facilities normally have Manufacturing Execution Systems (MES) that handle production activities, and EMSs that handle energy related activities such as monitoring the status of lights, HVACs, exhaust fans, power meters, substations, and flow meters (which include those for natural gas, compressed air, chilled water, and steam) and provides real-time energy consumption information. Other than the default configurations, the plant's EMS can also provide control functions such as occupied/unoccupied for building services [15] [16] [17]. Historically, EMS and MES have been isolated systems. Production, quality, and other operational data resides in separate databases from facility energy consumption data. The integration of these data and systems make it possible to take into account all the complexity and interaction of all energy consumed within the whole factory floor. The integration also provides opportunities to improve both productivity and energy performance for manufacturing firms to achieve sustainable manufacturing. Figure 2 shows such concept for energy demand control in industry facilities.

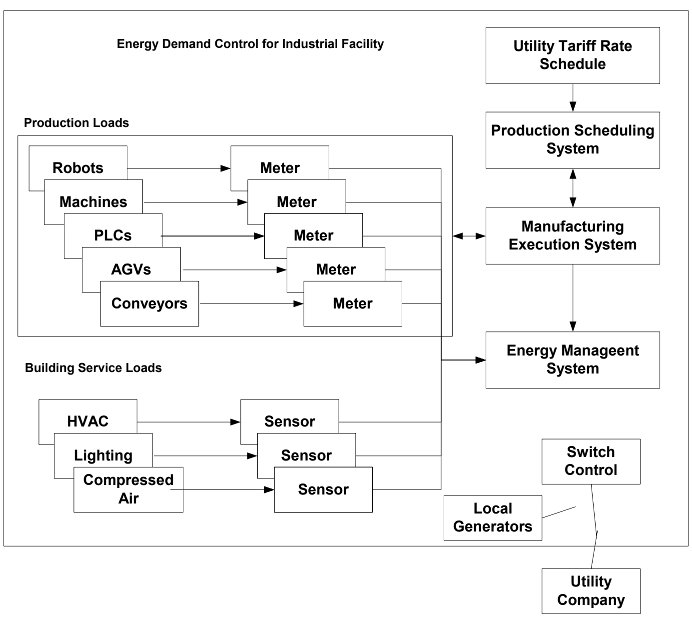


Figure 2. EMS-MES integration for energy demand control in industrial facilities

The challenge to deploy the DG-EMM framework and extend the plant's conventional EMS and MES involves defining and acquiring the data collection mechanisms to allow the DGMS to provide effective assessment and decision making for operational and investment recommendations. The system will provide facility energy managers with optimal actionable recommendations, and receive inputs from the managers such as constraints and priorities, the iterative process continues until the manager is satisfied with a recommendation and decides to implement it. To utilize the data acquired through EMS and MES making optimal operational decisions on energy management, we need to extend the capabilities of existing EMS by integrating it with DGMS. The result of the integration will help decision making such as:

- Benchmark processes/facility
- Evaluate performance trends
- Validate utility bills
- Assess equipment/process/building energy consumption
- Assess power system capacity
- Reduce peak demand and power factor penalties
- Maximize power system use
- Evaluate alternative renewable energy suppliers
- Evaluate sustainability capital equipment investment and alternative strategies
- Create cost saving and efficiency targets
- Develop plans according to the analysis results
- Allocate costs to encourage savings

Sustainability Investment Advisor

The development and deployment of energy efficient manufacturing technology requires making a range of decisions by facility managers on optimal mixes of investments and operational energy management. These decisions may be both very complex and unique for various manufacturers. There is a large range of energy management technologies available today, e.g., renewable energy sources, local generators, energy storage systems, highly efficient HVAC systems, energy harvesting solutions, and soon charging stations for EVs. What mix of these technologies achieves sustainability conformance? What interrelated contractual arrangement should the company make with power and gas utilities, as well as load curtailment companies for energy efficiency manufacturing? How do we assess the total energy cost, renewable energy credits, and savings and ROI for a particular mix of investments and contractual terms? How do we recommend an optimal mix, e.g., with maximum ROI subject to budget limitations over time? Unfortunately, simple answers such as "introducing technology X typically saves Y%," do not work for any non-trivial system since the technology components are highly interdependent and may involve complex interactions among them. To do the assessment, one needs to analyze historical and projected energy consumption demand patterns (e.g., per device, over space and time). Then, a baseline must be computed, which is what the consumption and costs would be without introducing new technologies. Finally, one needs to assess the consumption and costs with the new technology mix introduced. The last part is particularly challenging: we need to assess the consumption not per historical energy consumption pattern, but for optimally scheduled and configured energy demand. For example, if one introduces energy storage and local generation, the company could commit to a much higher level of curtailment that would have higher economic rewards. The company may schedule an interruptible load, e.g., cooling or heating water within the peak demand bounds. The company may decide that significant solar generation, which is highly interruptible, could be compensated with local generation. Both the assessment of savings (energy, emissions, cost) for a particular mix of energy efficient technologies and a recommendation for the "best" mix require considerable formal modeling, decision optimization, and statistical learning software solutions [13].

Clean energy (renewable energy) technologies are growing rapidly in response to a variety of critical drivers, which include exponential growth in world energy demand, concern about pollution of the environment, highly volatile fossil-fuel prices, and technological advances that are improving the performance and lowering the costs of renewable energy systems. It is critical to develop metrics and models to assess and evaluate clean energy technology products such as:

- Renewable energy technology products: Build an optimal renewable energy model that minimizes the cost/efficiency ratio and determines the optimum investment of different renewable energy sources such as wind energy, solar-photovoltaic and solar-thermal products, geothermal systems, and biomass conversion for liquid bio-fuels. What will be the optimum mix of renewable and storage resources? What will be the optimal mix of hybrid renewable and natural gas systems to compare economically with electric only systems?
- Energy storage products: Energy storage enables a shift of consumption to off-peak periods without impacting on the operation of the productive process. These may be compressed-air energy storage, rechargeable batteries and their application in clean energy vehicles PHEV, superconducting magnetic energy storage, and fuel cells and hydrogen energy storage, or thermal energy in a storage tank for heating water, air, or oil, if required. The plant usually draws power from the grid during the off-peak period to charge the equipment, which is subsequently discharged during the period of peak demand. The direct storage of electricity through batteries needs to be evaluated for the cost and the optimal charge/discharge cycle. Optimal investment evaluation for the mix of these technology products can be modeled using DGQL.
- Stand-by/local power generation: Because of the high cost of electricity during peak periods, local electricity generation can be economical. An optimal solution needs to be obtained as investment and operating constraints are often very complicated. All ancillaries such as location and amount of space required, motor preheating and cooling, emissions, noise, and vibration insulation have to be taken into account. Local generators are connected to the factory using switch control interface during peak demand periods or in case of any malfunction with the distributor's supply [18].

REQUIREMENT ANALYSIS OF DGQL MODELING FOR DEMAND CONTROL IN MANUFACTURING

A variety of opportunities exist within factory plants to reduce energy consumption or improve energy efficiency in order to lower cost while maintaining or enhancing the productivity of the plant. For example, energy cost can be reduced by minimizing the use of electricity during the peak demand periods. Electric demand management relates to electric tariff rates, new power generation, and incentives to curtail peak usage. The following classes of decisions regarding energy consumption, carbon emissions, and operational costs can be made through the integration of EMS and DGMS/DGQL [13].

- Optimal settings of the target peak demand and curtailment commitment: A high peak demand target may be prohibitively expensive, it could lead to less interruption of power and cheaper per kWh rates; whereas, a low peak demand target may lead to more interruption and the need to shed load, using local generation, buying power on the spot market, or any mix of the above.
- Optimal control of supply and/or demand in response to unforeseen changes: For example, a solar energy supply can be interrupted (e.g., on a cloudy day), a curtailment signal from a utility, or demand may increase (e.g., due to extreme weather). The response may involve load shedding to decrease consumption, using local generation, on-site storage, buying on the spot market, or any mix thereof.
- Optimal scheduling of consumption through aggregation and/or prioritization: For situations such as low-priority, interruptible manufacturing processes, on-site battery charging, or ice production for cooling, one would like to enable such consumption during off-peak hours and below peak demand target. Also, the schedule should be arranged to guarantee potential curtail energy, which will generate revenue that exceeds the average per kWh cost. These decisions must be optimally made while taking into account business constraints such as due date for production.
- Optimal load shedding: Load shedding of electricity consumption is to postpone some low-priority activities so as not to exceed the contractual threshold over the period. Such common loads include electric hot-water heaters, air conditioners, fans, and lighting zones. For example, depending on the thermal inertia of buildings, HVAC should be used during the off-peak rate period to pre-heat or pre-cool premises. Process rescheduling is more appropriate for facilities that operate on two or three shifts. If two or more production lines are involved, the operation cycles can be modified to avoid their coincidence at peak time. An optimization solution that combines all the

interactions is needed to determine the best load shedding schedules.

- Optimal demand control: The control of loads is performed by means of rules that optimize power reduction or disconnection from the grid on the basis of a pre-established limit regarding the maximum load. A large amount of dynamically collected data is the basis to make valid optimal decision.

Figure 3 shows a DGQL/SQL combined functional diagram for energy management in manufacturing facilities.

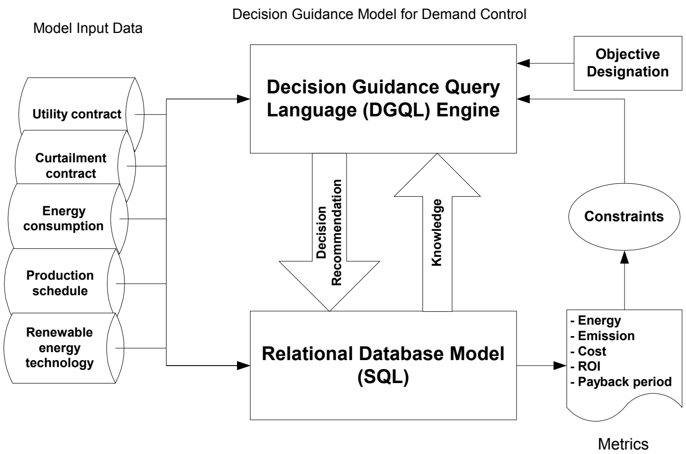


Figure 3. DGQL/SQL combined functional diagram

Model Inputs

In Figure 3, the inputs to the model are utility contract, curtailment contract, energy consumption from both production loads and building service loads, production schedule, and renewable energy technology data. These input data may be obtained from contracts, an Enterprise Resource Planning (ERP) system, MES, EMS, meters, sensors, products specifications, weather data, building data, or the utility company's WebPages. Further explanations are listed below:

- Energy consumption data: Basic historical electricity consumption data overtime for different levels, i.e., plant level, floor level, production line level, and equipment level. The data then can be graphed and analyzed, and peak demand can be determined.
- Meter data: Data may come from energy meters and submeters, which may include electricity, chilled water, steam, gas, fuel, water, and other metered resources.
- Utility contract data: Billing data from which different rates can be determined, such as how much the company pays for peak usage and what the normal rates are.
- Curtailment contract data: information about how much reward the company receives from curtailment commitment
- Stand-by generators data: information about the capacity, type, price, efficiency curves of the local generators, conditions, and constraints.
- Schedule data: Production line schedules, facilities schedules, and personnel schedules.

Model Logic Flow

As discussed earlier, the DGQL modeling is very similar to the traditional SQL modeling. First, the input data needs to be processed and formatted in R-DBMS. SQL schemas and views that compute metrics such as energy consumption, emissions, and cost need to be developed. The views can be annotated by indicating that some of the table columns are unknown, while another view can be annotated to indicate that the value it computes is to be used as an optimization objective in DGQL. With constraints on these metrics (e.g., budget limit, minimal energy) and objective defined (e.g., minimal cost, lowest emission), the optimization problem can be formulated and solved. SQL knowledge is the basis for inputs to the DGQL engine. The decision recommendation then returns to the database table where the results can be retrieved by the user through SQL queries. Any database application developers are capable of implementing the DGQL applications.

Model Metrics and Optimization Objective

DGQL views need to be developed to compute metrics for baseline and alternatives. Often, the difference between the metrics will be used as the objective. For example, the saving can be the difference between the current total cost and the future total cost derived by implementing certain improvement option, to maximize the saving can be one of the optimization objectives. The investment cost may include energy cost, equipment (such as generators, solar panels) cost, maintenance cost, and fuel cost. The revenue can be the curtailment rewards. ROI and payback period can be calculated. Emission reduction can also be computed. By knowing the rate at which a generator or other engine consumes fuel, a very accurate calculation of carbon dioxide (CO_2) emissions can be obtained. For example, every gallon of diesel fuel contains 2,778 grams of pure carbon. Every gram of atomic carbon, when oxidized with oxygen, forms 3.666 grams of carbon dioxide. Therefore, we can multiply the amount of carbon per gallon of diesel by the ratio of carbon weight to CO_2 weight by 99 percent, which is the percentage of the fuel that will oxidize [19].

$$CO_2 = 2{,}778 \text{ g} \times 3.666 \times 0.99 = 10{,}082 \text{ g}. \quad (1)$$

That is, each gallon of diesel fuel produces, on average, 10,082 g of CO_2, or about 22.2 lb of CO_2.

DGMS/DGQL Methodology Procedures

The DGMS/DGQL methodology involves several activities. The detailed steps are listed below.

1. Define an energy management or investment/planning problem by setting up objectives and scope
2. Identify the key performance indicators and their metrics for the problem
3. Identify input data required for the modeling

4. Collect historical data (energy consumption from the production system, utility contract, and curtailment contract data)
5. Understand core EMS database structure and how to augment and extend it with the database structure of the DGMS
6. Integrate the manufacturing process energy data collection with the EMS and DGMS
7. Determine controllable parameters
8. Process the raw data to extract the useful subset
9. Develop R-DBMS schemas and populate the tables
10. Identify/develop algorithms to compute metrics
11. Develop database views to calculate metrics
12. Formulate optimization problem using DGQL
13. Create test scenarios
14. Obtain optimal solutions
15. Develop plan and act based on optimization results

A CASE STUDY: DGQL MODEL FOR DEMAND CONTROL OF A MANUFACTURING FACILITY

A simple DGQL model of demand control for a manufacturing facility is discussed and implemented to demonstrate the proposed methodology.

Electricity costs differently at different times of the day. Peak electric demand is a significant component in the cost of electricity. Electricity for most industrial facilities has two types of charges: energy cost that is measured as kilowatt hours (kWh) and a demand cost measured at kilowatts (kW). It is Tariff Rate Schedule (TRS) in utility terms. There will be potential opportunities for demand control in the following cases [8]:

- The facility has production loads that operate less than 24 hours per day.
- The electric load profile shows demand peaks.
- There are equipment loads that can be interrupted for a period of more than 15 minutes.

From the company's utility contract, the TRS can be analyzed. Table 1 is an example tariff table. The demand portion of the energy cost is $16.00 per kW, which means that the utility company measures the electricity usage every 15 minutes for the whole month, the peak energy use of the month is called the demand and is multiplied by $16.00 to determine the demand charge. Every kW reduced from this peak is worth $16.00. The energy manager of the facility decides the peak demand. Shifting some equipment/machine usage to the periods of lower cost or using stand-by local generators during the demand period can save a huge amount of money. Decisions also need to be made for curtailment commitment and what generator to buy and how many are needed. Analyses of these options are important to the decision makers in order to make decisions to avoid unnecessary high cost of energy and equipment.

Case Study Setting

The objective of this case study is to model part of the demand control using DGQL and provide recommendations on energy usage patterns, number and types of generators needed, and optimal curtailment amounts to maximize savings and minimize energy consumption and emissions.

The case study scenario and some data are adopted from [9]; the plant has a curtailment energy purchase contract with its utility company. The facility needs local gas combustion turbine generators (CTG's). If the standby generator output is lower than plant load, the facility must either shed load or provide for a contractual utility supply of up to the difference during curtailments.

Table 1: An example tariff table

Time Period	Energy Cost	Unit
Peak Demand Load (1600 kW): 8am – 8pm Monday- Friday	$16	kW
On Peak : 8am – 8pm Monday-Friday	$ 0.08	kWh
Off-Peak: 8pm – 8am Everyday	$0.06	kWh

Raw data (e.g., metering data, production and building service loads energy consumption) are from facility EMS, utility bill and contract (dynamic pricing), curtailment contract (curtailment level and revenue), local generator specification (e.g., capacity, fuel consumption requirement, price, and maintenance cost), and loads schedules (both production and building service loads). Different types of generators have different power generation capabilities, annual maintenance cost, fuel needs, and prices.

Energy suppliers include utility companies, spot market, stand-by generator, on-site storage, renewable energy sources. Energy demand includes production system and buildings services within the facility.

To determine monthly savings, first, from the curtailment contract, the revenue is determined by the level of commitment. Then, we use historical energy consumption data per interval to come up with the actual consumption costs. We use monthly accumulated usage to determine peak demand price. The usage of local generators reduces per interval consumption, which leads to a cost reduction, and consequently, the monthly target peak demand is reduced, this, in turn, lowers the per peak demand price. Generator prices, maintenance cost, and fuel cost need to be considered as cost. The optimization problem is to maximize the savings, which is the difference between total cost and revenue [13]. Relationships of computation elements of the model are shown in Figure 4 and Figure 5. For example, the emission can be calculated through energy and fuel consumed from both the operational and maintenance aspect. It can be also calculated through life cycle analysis of a product or a process.

To determine the savings, payback period, and ROI for a simplified case, we use the formulas below.

Savings = current cost – future cost
= (total operational cost + maintenance cost) – (predicted operational cost + investment cost + predicted maintenance cost – curtailment revenue) (2)

Payback period = generator investment/annual savings (3)

ROI = savings/generators investment (4)

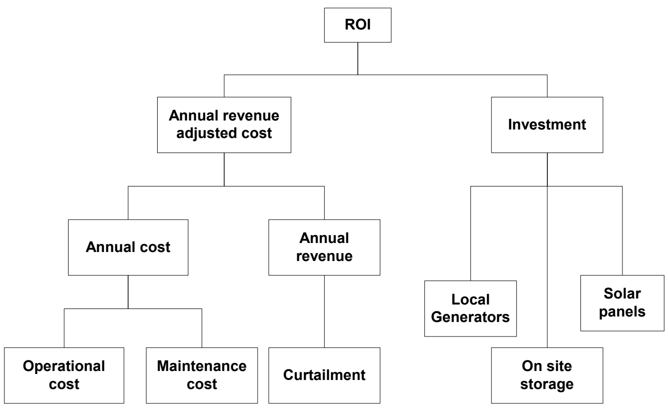


Figure 4. Relationship of computation elements for ROI

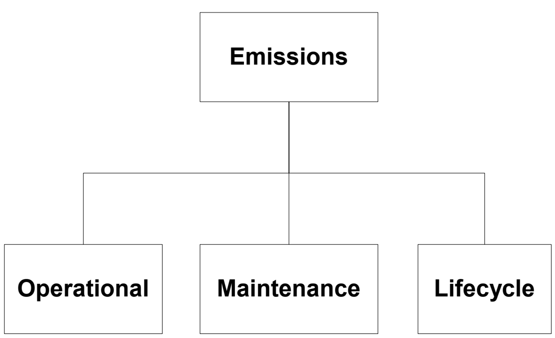


Figure 5. Relationship of computation elements for emission

If the investment does not have a positive ROI, or if the payback period is too long, then the investment should not be undertaken.

DGQL Data Model

As shown in Figure 3, based on the case scenario, performance indicators and metrics, optimization objective, and constraints, input data schema tables need to be defined, and metrics calculation data views need to be developed. DGQL optimization views provide the solutions.

DGQL Input Tables

Some of the input tables are given below. Decision variables are shown in italics. These are the variables for which the DGQL system will do instantiation and produce optimal values. For every supply type, find parameters that allow computing costs, and emissions.

- Schedule (interval, account, KW, *on_flag*)
  - Interval: 15 minutes time slot
  - Account: any suppliers that produce power or loads that consume power
  - KW: supply adds KW and demand subtracts KW
  - On_flag: 1 if the account is enabled, 0 if the account is disabled
- supply (interval, account, KW, on_flag, solar_cost)
- predicted_demand (interval, account, KW, on_flag)
- utility_contract_decision (account, *peak_demand*)
- utility_contract_per_KWH (account, season, day_peak_flag, KWH_cost)
- utility_contract_per_peak_demand (account, demand_bound, MW_charge)
- curtailment_intervals (interval, baselineKW, KW, *curtailment_commitment*)
- max_interruptions_per_account (account, max_interruptions)
- minimum_curtailment (min_curtailment, min_reward)
- curtailment_graph (bound, rewards_per_MW)
- controllable_loads (id, name, priority, max_interruptions)
- local_generators (id, price, maint_cost, min_output, max_output, max_fuel_required, min_fuel_required, name, fuel_cost)
- local_generator_efficiency_curve (generator_id, seq_no, tangent, left_x)
- local_generator_purchase (id, *qty*)
- solar_panel (id, *qty*)

DGQL Output Tables

Some of the output tables are given below. For every supply type, find parameters that allow computing costs, emissions.

- total_vs_peak_from_grid (interval, total_from_grid, peak_demand)
- predicted_curtailment_per_interval (interval, curtailment_flag)
- from_grid_schedule (interval, KW)
- prev_vs_current (prev_interval, prevKW, interval, KW, curtailment_KW)
- curtailment_revenue = min_reward + (x-min_curtailment) * rewards_per_MW
- Cost computation (cost)
- Maintenance cost (cost)
- Total cost per type (amount)
- Total savings (savings)
- Proposed ROI (percent)

- Total emissions (amount)

DGQL Constraints

Some of the constraints are given below.

- Total supply = total consumption (for every interval)
- Source that are both supply and demand (e.g., energy storage) must satisfy that either supply is on or demand is on, but not both for every time slot
- The total power expected from generators during curtailment must not exceed the total generator capacity of all generators
- Total_from_grid < = peak_demand
- KW <= base_line_KW – curtailment_commitment

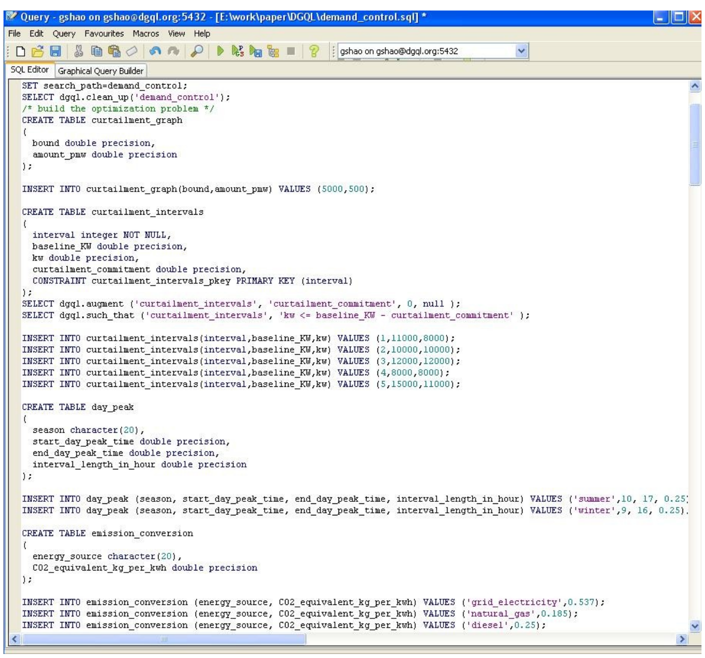
DGQL Views

The goal of the model is to find the maximum savings, ROI and minimum emission, assuming given curtailment commitment, peak demand setting, and investment for local generation. According to (2), (3), and (4), step by step computations are needed.

For example, one of the DGQL optimization views is shown as below:

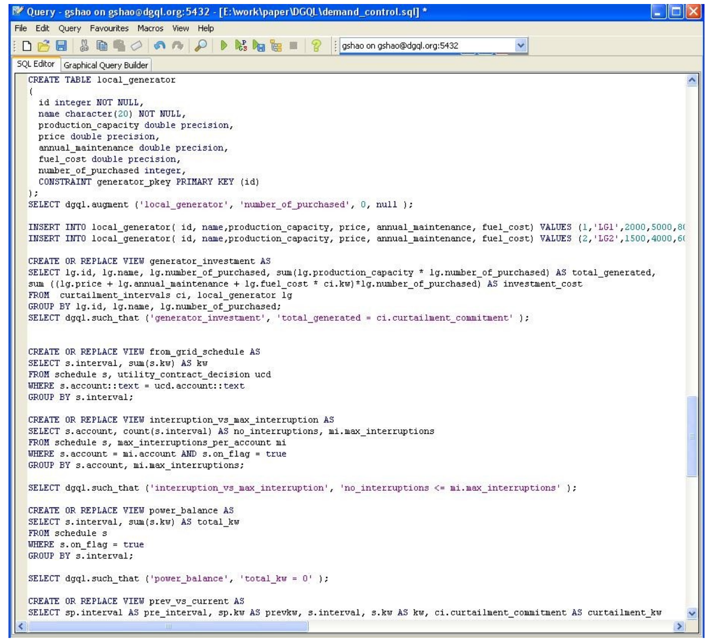
```
SELECT *
FROM dgql.maxmize (savings);
```

Figure 6 and Figure 7 are examples of the DGQL table and computation views. Currently, the input data are testing data. By replacing the testing data with a company's real data, the decision recommendations, which are the optimal results, will be derived.



```
SET search_path=demand_control;
SELECT dgql.clean_up('demand_control');
/* build the optimization problem */
CREATE TABLE curtailment_graph
(
  bound double precision,
  amount_pmw double precision
);

INSERT INTO curtailment_graph(bound,amount_pmw) VALUES (5000,500);

CREATE TABLE curtailment_intervals
(
  interval integer NOT NULL,
  baseline_KW double precision,
  kw double precision,
  curtailment_commitment double precision,
  CONSTRAINT curtailment_intervals_pkey PRIMARY KEY (interval)
);
SELECT dgql.augment ('curtailment_intervals', 'curtailment_commitment', 0, null );
SELECT dgql.such_that ('curtailment_intervals', 'kw <= baseline_KW - curtailment_commitment' );

INSERT INTO curtailment_intervals(interval,baseline_KW,kw) VALUES (1,11000,8000);
INSERT INTO curtailment_intervals(interval,baseline_KW,kw) VALUES (2,10000,10000);
INSERT INTO curtailment_intervals(interval,baseline_KW,kw) VALUES (3,12000,12000);
INSERT INTO curtailment_intervals(interval,baseline_KW,kw) VALUES (4,8000,8000);
INSERT INTO curtailment_intervals(interval,baseline_KW,kw) VALUES (5,15000,11000);

CREATE TABLE day_peak
(
  season character(20),
  start_day_peak_time double precision,
  end_day_peak_time double precision,
  interval_length_in_hour double precision
);

INSERT INTO day_peak (season, start_day_peak_time, end_day_peak_time, interval_length_in_hour) VALUES ('summer',10, 17, 0.25
INSERT INTO day_peak (season, start_day_peak_time, end_day_peak_time, interval_length_in_hour) VALUES ('winter',9, 16, 0.25).

CREATE TABLE emission_conversion
(
  energy_source character(20),
  CO2_equivalent_kg_per_kwh double precision
);

INSERT INTO emission_conversion (energy_source, CO2_equivalent_kg_per_kwh) VALUES ('grid_electricity',0.537);
INSERT INTO emission_conversion (energy_source, CO2_equivalent_kg_per_kwh) VALUES ('natural_gas',0.185);
INSERT INTO emission_conversion (energy_source, CO2_equivalent_kg_per_kwh) VALUES ('diesel',0.25);
```

Figure 6. An example DGQL table screen



```
CREATE TABLE local_generator
(
  id integer NOT NULL,
  name character(20) NOT NULL,
  production_capacity double precision,
  price double precision,
  annual_maintenance double precision,
  fuel_cost double precision,
  number_of_purchased integer,
  CONSTRAINT generator_pkey PRIMARY KEY (id)
);
SELECT dgql.augment ('local_generator', 'number_of_purchased', 0, null );

INSERT INTO local_generator( id, name,production_capacity, price, annual_maintenance, fuel_cost) VALUES (1,'LG1',2000,5000,8
INSERT INTO local_generator( id, name,production_capacity, price, annual_maintenance, fuel_cost) VALUES (2,'LG2',1500,4000,6

CREATE OR REPLACE VIEW generator_investment AS
SELECT lg.id, lg.name, lg.number_of_purchased, sum(lg.production_capacity * lg.number_of_purchased) AS total_generated,
sum ((lg.price + lg.annual_maintenance + lg.fuel_cost * ci.kw)*lg.number_of_purchased) AS investment_cost
FROM  curtailment_intervals ci, local_generator lg
GROUP BY lg.id, lg.name, lg.number_of_purchased;
SELECT dgql.such_that ('generator_investment', 'total_generated = ci.curtailment_commitment' );


CREATE OR REPLACE VIEW from_grid_schedule AS
SELECT s.interval, sum(s.kw) AS kw
FROM schedule s, utility_contract_decision ucd
WHERE s.account::text = ucd.account::text
GROUP BY s.interval;

CREATE OR REPLACE VIEW interruption_vs_max_interruption AS
SELECT s.account, count(s.interval) AS no_interruptions, mi.max_interruptions
FROM schedule s, max_interruptions_per_account mi
WHERE s.account = mi.account AND s.on_flag = true
GROUP BY s.account, mi.max_interruptions;

SELECT dgql.such_that ('interruption_vs_max_interruption', 'no_interruptions <= mi.max_interruptions' );

CREATE OR REPLACE VIEW power_balance AS
SELECT s.interval, sum(s.kw) AS total_kw
FROM schedule s
WHERE s.on_flag = true
GROUP BY s.interval;

SELECT dgql.such_that ('power_balance', 'total_kw = 0' );

CREATE OR REPLACE VIEW prev_vs_current AS
SELECT sp.interval AS pre_interval, sp.kw AS prevkw, s.interval, s.kw AS kw, ci.curtailment_commitment AS curtailment_kw
```

Figure 7. An example DGQL computation view screen

CONCLUSION

A growing number of manufacturing industries are initiating efforts to address sustainability issues. Energy management and investment decisions for improving energy efficiency require predicting behavior of a complex system and making decisions to direct the system towards desirable outcomes. These include reducing energy consumption and carbon emissions, and saving operational costs, while maintaining a desirable production level. In such applications, predictions and decisions are to be made in the presence of large amounts of dynamically collected data and learned uncertainty models. This paper proposes a DG-EMM framework to perform what-if analysis and make optimal actionable recommendations for a manufacturing facility. The proposed DG-EMM will support user-defined objectives for optimal recommendations, such as minimizing emissions, minimizing energy costs, and maximizing ROI. The optimal balance between predicted energy demand and cost-optimized, sustainable energy supply can be determined.

This paper also reviewed the fundamental requirements of DGQL modeling for energy management and discussed various components such as the objective, scope, model elements, and its input and output requirements for DGQL modeling implementations. DGQL analysis helps make decisions for manufacturers to sustain the savings and obtain more energy efficiency from buildings, equipment, and production processes within the plant. A case study of the peak demand control for an example manufacturing facility was discussed. It allows assessing the investment options using historical data as input and evaluating different options for an optimal decision making in capital equipment investment.

DISCLAIMER

No approval or endorsement of any commercial product by the National Institute of Standards and Technology is intended or implied. Certain commercial software systems are identified in this paper to facilitate understanding. Such identification does not imply that these software systems are necessarily the best available for the purpose.

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