Methods For Estimating System Demand For Design & Peak Conditions

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Western Regional Gas Conference, August 2011

Abstract

Several methods are presented for estimating system demand for use with computer modeling a natural gas system under design and/or peak conditions.

Introduction

Modeling of a natural gas system allows conditions and configurations in an actual system to be simulated in a non-operational environment. For the purposes of this paper, modeling shall refer to computer modeling of a gas system using specialized network modeling software. These software use various mathematical representations of the system components to represent the system within the computer environment, simulating the pressure and flows in the system, and the response of the system to changes in demands and configurations.

System models are used as both a design and an operational tool, generally to answer what-if questions about the system. For example, what if we add this new subdivision, what if we remove this section of line from service, can we retire this regulator station, what is the best location for a new gate station, what size should be used to replace this leaking main. Often the data used to answer design questions are different than the criteria and data used to answer operational questions.

Design modeling can be considered to basically involve modeling for pipe sizing, pipe configuration, and regulator/supply placement to accommodate system extension or replacement activities - looking at a future system. Operational modeling involves modeling for configuration changes to an existing system (valve closures, removing regulator or gate stations from service, removing segments from service), modeling for set/supply pressure and flow changes, and troubleshooting operational issues (low pressure incidents etc). There are a number of similarities between design modeling and operational modeling. However the demand portion of the model, the customer loads, is often different depending on the intended purpose of the model. This paper will present several methods for estimating the appropriate demand values.

The System Model

In a sense, a “system” model consists of two separate “models” - a configuration model, and a demand/load model. The configuration model consists of data describing the physical system - basically the hardware of the system. Configuration data includes items like pipe size, connectivity, regulator locations and set pressures, and supply locations and pressures. The demand model consists of data describing the load and usage information associated with the gas appliances and equipment connected to the system. Demand data includes information about total connected load, load diversity and coincidence, cumulative usage (daily, monthly or annual), and ideally some knowledge of the demand response to temperature changes.

Developing The Configuration Model

Developing the configuration portion of the system model is fairly straight forward. In the basic sense it simply involves copying the piping layout from a paper map, CAD drawing, or GIS data into the modeling software to create the configuration portion of the model. This data usually includes the main and service locations, connectivity, pipe sizes, and regulator and supply locations. In most cases this information is relatively stable and doesn’t change all that often or quickly, making it fairly easy to obtain a “snap shot” of the system configuration.

Developing The Demand Model

Developing the demand portion of the system model is not so straight forward. The demand on the system changes constantly, due to changing weather and usage conditions. In order to obtain usable results from the system model, it is important to apply an appropriate demand model. The demand model can consist of several components. Some these components listed below.

Some of the individual components of the demand model are described in the following.

Total Connected Load

The total connected load (TCL) for a customer refers to the summation of the "badge" ratings for all of the gas appliances at a specific location. The TCL can be separated into several general categories.

Heating/Temperature Sensitive load - Load which is affected by changes in outside temperature.

Domestic load - Load which is used for domestic tasks like water heating, clothes drying, cooking.

Discretionary load - Load which is occasionally used like patio heaters, gas grilles, gas logs.

Industrial/Process load - Load that once started, remains on for an extended period at a generally steady consumption.

Seasonal load - Load which may be temperature sensitive, but is only in use during certain seasons, for example load from pool heaters, gas fired air-conditioning, ice melting.

Diversity/Coincidence

Load diversity refers to the difference in load usage characteristics. For example, heating load usage is significantly affected by outside temperature, where as hot water heating is more affected by human activity and is somewhat temperature independent. Cold weather will cause the heating load usage to increase, while it will have little affect on the water heating usage which will remain relatively consistent.

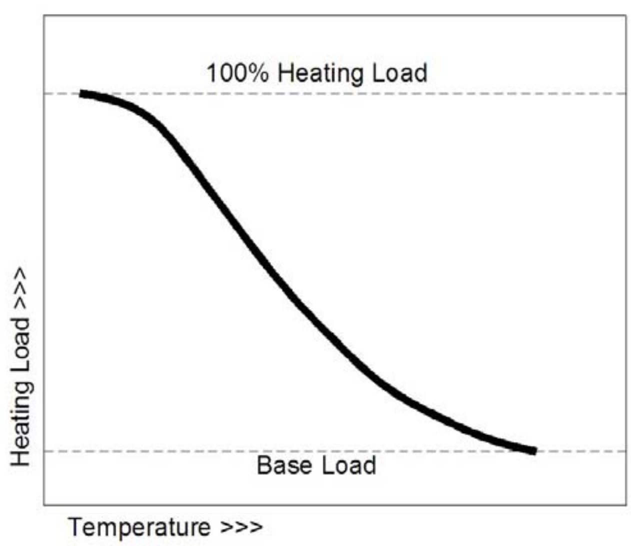
Coincidence is basically the opposite of diversity - Coincidence refers to the similarity in load. Or in terms of gas system modeling, it refers to how much of the load is in simultaneous service. It is usually expressed as a factor or percentage of the TCL or some other reference load.

Cumulative Usage

Cumulative Usage refers to the total gas usage over a given period of time. For example the usage over a monthly billing period, or perhaps a daily or an annual usage value for a customer or an entire system.

Demand/Temperature Response

The Demand/Temperature Response refers to the change in usage of heating/temperature sensitive loads in response to changes in outside temperature.



Demand Model Methods

The demand components are manipulated by various methods to develop the demand values used in the system model. These methods vary widely in complexity and effectiveness. Some of the more common demand modeling methods are described in the following.

Proration Method

The Proration method proportions the total cumulative usage for a specific period to each individual customer. The theory of the method assumes that the proportion of gas used over the cumulative period for a specific customer, is similar to the proportion of gas used for a specific "instantaneous" period. For example, if a customer uses 1% of the total monthly volume, then that customer is assumed to use 1% of the peak hour load for the same period.

$$Xcustomer = \frac{Qcustomer}{Qtotal}$$

$Xcustomer =$ *Customer proportion factor*
$Qcustomer =$ *Individual customer usage*
$Qtotal =$ *Total of all customer usage*

When using this method it is important to ensure that the cumulative period is representative of the instantaneous period to be modeled. For example, that if the instantaneous period is associated with a peak heating hour, the cumulative period should also be for a peak heating period, one which preferably includes a peak hour occurrence.

To apply this method, the prorated demand value for each customer is computed, then the total demand value is applied. For example, the desired or predicted total peak hour consumption for the system is multiplied by each customer's prorated value to obtain the predicted peak hour demand for each customer.
When actual cumulative usage values are not available, this method can also use the Total Connected Load, meter size, or building size to establish the proration values.

$$QPEAK_{customer} = X_{customer} \times QPEAK_{total}$$

$QPEAK_{customer} =$ *Individual peak customer demand*
$QPEAK_{total} =$ *Total demand for all customers*
$X_{customer} =$ *Proportion factor for customer*

Load Factor

The Load Factor method uses one or more pre-defined factors to convert specific data values to demand values usable by the system model. For example, a factor is used to convert annual cumulative usage to a monthly value, or a factor is used to convert a monthly value to a daily value, or a factor is used to convert a daily value to a hourly value.

$$Q_{day} = Q_{month} \times LOADFACTOR_{month\_day}$$

$$LOADFACTOR_{month\_day} = \frac{1}{22}$$ *(Representative value)*

$$Q_{hour} = Q_{day} \times LOADFACTOR_{day\_hr}$$

$$LOADFACTOR_{day\_hr} = \frac{1}{16}$$ *(Representative value)*

$Qmonth =$ *Peak monthly consumption*
$Qday =$ *Peak daily consumption*
$Qhour =$ *Peak hourly demand*
$LOADFACTOR_{month\_day} =$ *Load Factor to convert from monthly to daily values*
$LOADFACTOR_{day\_hr} =$ *Load Factor to convert from daily to hourly values*

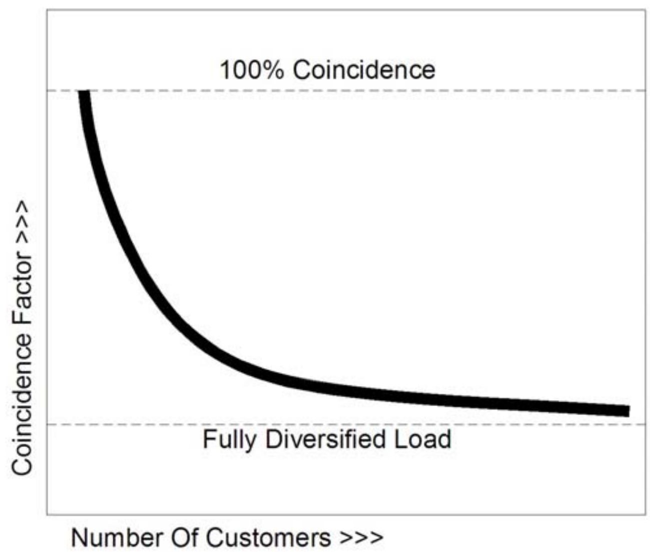
Care must be taken when establishing the various load factors. Except for extremely consistent industrial type loads it is generally not appropriate to divide the annual usage by the number of months in a year to obtain an estimate for peak monthly usage, or to divide the peak monthly load by the number of days in the month to obtain the peak daily load. The same is true for the peak hourly load, the daily load is not divided by the number of hours in the day to obtain a peak hourly load. In the case of a monthly to daily conversion, a factor of about 1/22 has sometimes been used. For converting from daily to hourly values, a factor of 1/18 to 1/16 has often been used.

The load factors are usually derived from metered volume data from an existing system. If sufficient records are maintained, factors can be developed to convert cumulative consumption for essentially any period to consumption or demand for another.

Coincidence Factor

The Coincidence Factor method uses predefined factors to estimate the peak hour demand. A coincidence factor usually represents the portion of the total connected load simultaneously in use for a given number of customers as a factor or percentage. For a single customer, it is likely that 100% of their total connected load is in use sometime during a peak period. For example both their furnace and hot water heater may be running at the same time. Although this would also be true for their neighbors' appliances, this condition doesn't necessarily occur at exactly the same point in time for every customer. The simultaneous use of the appliances is referred to as the coincident load. As the number of customers increases, the chance that their appliance will be in simultaneous use becomes less, decreasing the coincident load.

For a single customer, the coincidence factor is 100%, for 100 customers the coincidence factor might be 75%, and for 1000 or more customers it might be 60%. The coincident factor reaches some asymptotic value as the number of customers increases.



Coincidence factors can be based on actual operating or theoretic data and vary greatly based on region, construction type, and household make up. Coincidence factors are useful for working with temperature sensitive and domestic type demands, they are not appropriate for use with industrial type loads.

Degree Day

The Degree Day method estimates a demand based on an a curve fit of previous usage data and degree day information. A "degree day" refers to an index which represents the time duration of an average temperature different from a certain threshold or base temperature expressed in Fahrenheit per day. In the US gas industry it is common to use a base temperature of 65 degrees Fahrenheit and an average temperature over a 24 hour period. This use of the degree day definition is referred to as a "heating degree day".

$$DD = \left(T_{base} - T_{avg}\right) \times \Delta t$$

$Tbase$ = *Base temperature, Fahrenheit (Usually 65 in the US)*

$Tavg$=*Average temperature for the time period, Fahrenheit*

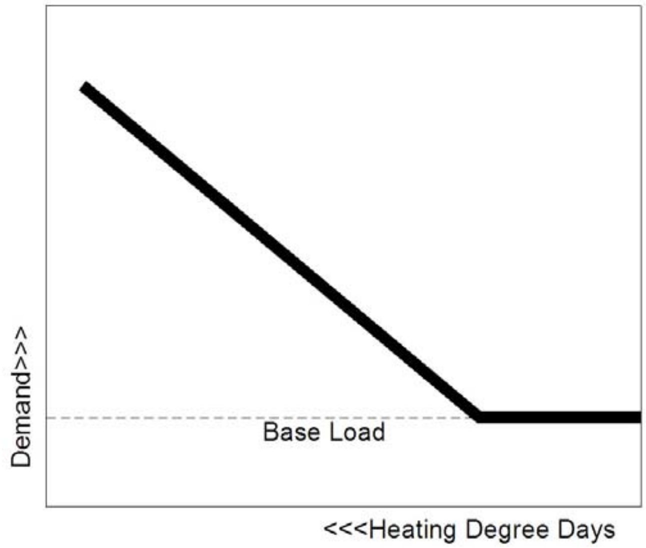
Δt =*Time period assocaited with the average temperature, days*

This method most often uses some sort of linear interpolation of the temperature sensitive demand indexed to heating degree day values. The method assumes that the temperature sensitive demand ranges from zero at a heating degree day of 0 (temperatures above 65 F) and increases linearly with an increase in heating degree day (decrease in temperature).

$$
\begin{aligned}
&DD < 65F \\
&\quad Q = A + B \times DD \\
&DD >= 65F \\
&\quad Q = 0
\end{aligned}
$$

$A, B =$ *Equation constants derived from statistical analysis of previous consumption*
$Q =$ *Heating demand corresponding to DD*
$DD =$ *Number of degree days*

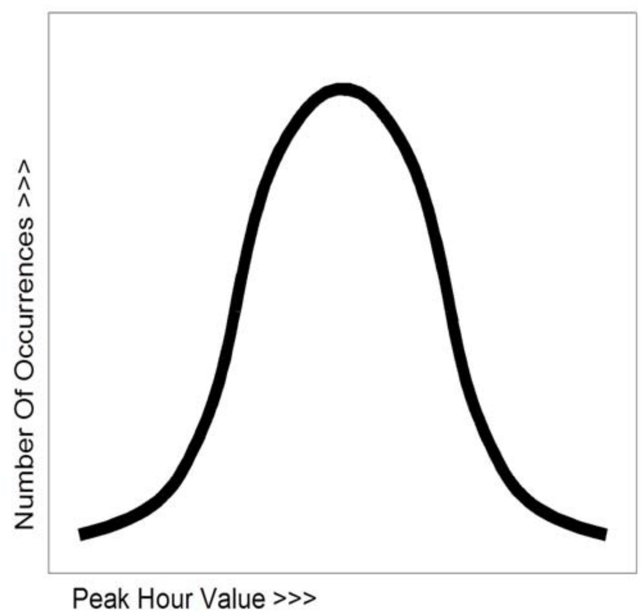
Actual temperature sensitive demands do not completely respond linearly to temperature. The demand is somewhat asymptotic at extremely cold and at warm temperatures. In between those extremes, the relationship is generally linear. At extremely cold temperature the demand approaches a value equivalent to 100% of the heating load being simultaneously in service. At warm temperatures, near the comfort zone where heating demand would cease, the demand approaches the "base" load value. The base load value is the demand that would be experienced by the system in the absence of heating load, it represents the load due to pilot lights and domestic usage.
The demand predicted by this method generally represents a monthly or daily load value and must be converted to a peak hour load, usually by applying a load factor to the predicted load.



This method is not applicable to industrial or seasonal load types.

<u>Diversity Curves</u>

The Diversity Curve method uses the concept of probability and a normal distribution curve to determine the most likely peak demand based on the number of customers present and their annual energy or gas consumption. This method incorporates the idea of coincidence, whereby not all loads are present at the same time. However it realizes that there is a chance that at some point there could be no demand (other than base load) in service, and that there is also a chance that at some point all of the load could be in service. It then attempts to predict the demand that would occur at some defined frequency. For example, it would predict the peak demand that could be expected to occur 98% of the time.



The parameters and constants used in the predication equations are based on empirical data derived from heating equipment type, annual usage, and customer count.

$$QPEAKcustomer = \left(A + \frac{B}{\sqrt{n}} \right) \times QANNUALcustomer$$

$A, B =$ Predetermined equation constants

$n =$ Number of customers in group

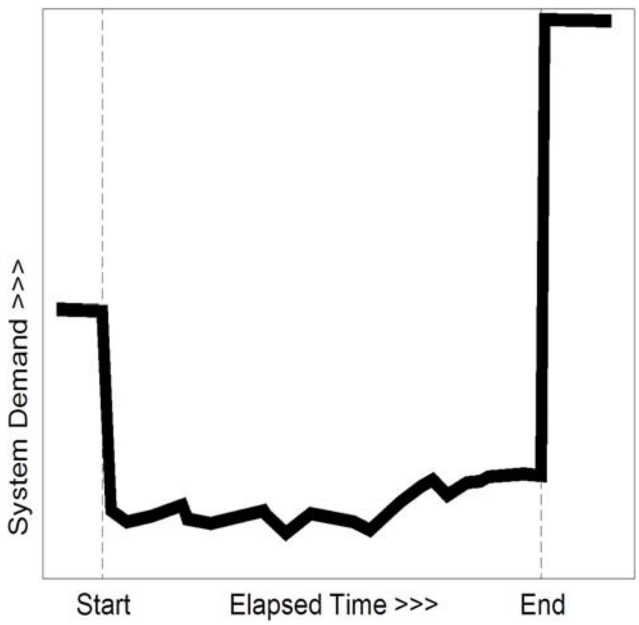
$QPEAKcustomer =$ Peak Customer Demand

$QANNUALcustomer =$ Annual Cumulative Consumption

This method is not applicable to industrial or seasonal load types.

Power Outage

The Power Outage method attempts to predict the demand which might occur after a sustained electrical power outage during moderate to extreme cold weather. The method assumes that during the power outage the space heating load will be suspended, however the domestic load would continue to operate as normal. When the power is restored, it is assumed that all of heating load in the affected area would resume operation.



Under this method a usage factor is determined for the heating and domestic portions of the total connected load. The factors are then either applied individually to different load types or combined and applied to the total connected load. For example, it might be assumed that 100% of the heating load and 30% of the domestic load would be in service directly after restoration of a power outage. If the customer had an 80 Mbtu/hr furnace and a 40 Mbtu/hr hot water heater, the resulting demand would be 1.00 x 80 + .30 x 40 = 92 Mbtu/hr. Or based on the total connected load, the associated usage factor would equal the resulting load divided by the total connected load, 92/120 = .77 or 77%.

$$QPEAKcustomer = \left(Qheat \times Xheat \right) + \left(Qdomestic \times Xdomestic \right)$$

$QPEAKcustomer =$ *Customer demand*

$Qheat =$ *Heating load rating*

$Xheat =$ *Heating usage factor*

$Qdomestic =$ *Domestic load rating*

$Xdomestic =$ *Domestic usage factor*

Different factors might be used for different customer counts or construction types. This method is not applicable to industrial or seasonal load types. And does not account for the situation where customers might try to supplement their space heat requirements using their gas logs or gas stove tops or ranges during the power outage.

Although this method has been traditionally used to predict the system demand following restoration of a power outage, a similar less extreme phenomena may also occur when setback or master controlled thermostats are used and essentially turn on a dormant heating demand for a group of homes or facilities at a near coincident time.

System Model Application

The purpose of the demand model is to develop demand/load values to be combined with the configuration model to create the system model. It is not unusual to use a combination of demand models to develop the overall demand model for a particular system or to represent a particular operating condition.

Generally the System Model is concerned with the system performance for a specific operational instance or specific set of conditions. For example the model may be attempting to predict system performance under "design" conditions, which may or may not be representative of actual operating conditions. Or the model may be attempting to predict system performance under actual peak conditions. Or the model may be attempting to predict the system performance under summertime conditions with one or more of the regulator stations out of service.

Depending on the conditions the model is trying to simulate, one demand model might be used to predict the residential and commercial space heating values, another for the seasonal demand, and a third for the industrial demand. The value produced by the demand model may need to be further manipulated to represent less than peak conditions.

In general the proration method can be used for all types of modeling. When used with the appropriate demand factor, the degree day method can be used with most modeling scenarios. The other methods tend to be more suitable for specific modeling conditions.

Regardless of the demand model method used, it is critical to have the system demand distributed properly. The various modeling applications handle the entry of customer demand in different ways, no matter the method of entry, the loads need to be applied to the configuration portion of the model as near as practical to their actual connection locations.

Demand Method Application...

Method	**Conditions**			**Notes**
	Design	**Normal Peak**	**Operations**	
Proration	✔	✔	✻✔	The Proration method can be used for most any condition when used with the applicable total load value.
Load Factor	✔	✻✔	✔	
Coincidence Factor	✻✔			
Degree Day	✔	✔	✔	The Degree Day method can be used for most any heating condition when used with the appropriate Load Factor.
Diversity Curves	✻✔			
Power Outage	✻✔			

✻ - Method specifically developed for indicated condition

✔ - Can be used for the conditions, but not specifically developed for the indicated condition.

Additional Considerations

There are few new and not so new technologies being used by homeowners and commercial customers that are adding some complexity to the effort to estimate or predict the system demand. A few are listed below:

Combination Boilers - This type of boiler provides both hot water for domestic and heating using the same boiler. This doesn't affect the peak demand so much, as it affects the base load or domestic heating load. Since the domestic hot water is being generated by a much higher rated unit than by a traditional stand alone hot water heating unit.

Tankless Hot Water Heaters - This type of domestic hot water heating unit only operates when there is a demand for hot water, so the random on/off that might occur with a storage tank type unit is eliminated. Further these units usually employ a much higher rated burner than a traditional stand alone unit. Possibly making a significant impact on the peak hour value, and a lessor impact on the base load value.

Setback Thermostats - These type of thermostats have been in use for a long time, however as their implementation becomes more abundant, when the morning startup time set close to the same time, they can tend to increase the diversity of the heating load startup, thereby increasing the coincidence of the load and increasing the overall peak hour value.

Central Heating Control - Similar to setback thermostats central control systems tend to turn on and off the heating load for a group of buildings at the same time. For example buildings associated with a large campus may have a central control system that reduces or turns the heat off for many of the buildings at the start of a weekend, the buildings cool down over the weekend and Monday morning the heat is turned up or on and all of the heating units come on at the same time - increasing the overall peak hour value for this group of buildings.

Modulating Boilers - These type of boilers (and furnaces) fire at different rates depending on the outside temperature. As the outside temperature decreases, the demand on the unit increases. This probably doesn't affect the peak hour value significantly, because that presumably occurs during fairly cold temperatures. However this variable can cause challenges when trying to model their demand during non-peak conditions.

Automated/Electronic Meter Reading - The use of automated and electronic meter reading technologies are becoming more abundant. There use doesn't affect the system demand, but it does offer an opportunity to study usage patterns for all variety of weather and operating conditions. In future, this data may be very useful in developing new and improved demand modeling methods.

Conclusion

It seems that much of the effort in developing a system model is often spent building the configuration portion of the model, to an extent this is necessary. However no matter how good the configuration model is, the overall system model will not be very useful if the demand portion of the model is of poor quality. It is often tempting to be lax in the demand modeling portion of the system model development, perhaps using guessed or average values, this can only produce "guessed" or "average" results. Important and costly decisions are often based on the results of a model, the effort used in developing the demand portion of the model should reflect the importance of these decisions.