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DUKE ENERGY OHIO EXHIBIT____

BEFORE

THE PUBLIC UTILITIES COMMISSION OF OHIO

In the Matter of the Application of Duke Energy Ohio, Inc., for an Increase in Gas Rates.	)))	Case No. 12-1685-GA-AIR
In the Matter of the Application of Duke Energy Ohio, Inc., for Tariff Approval.	)))	Case No. 12-1686-GA-ATA
In the Matter of the Application of Duke Energy Ohio, Inc., for Approval of an Alternative Rate Plan for Gas Distribution Service.	))))	Case No. 12-1687-GA-ALT
In the Matter of the Application of Duke Energy Ohio, Inc., for Approval to Change Accounting Methods.	)))	Case No. 12-1688-GA-AAM

DIRECT TESTIMONY OF

JOSE MERINO

ON BEHALF OF

DUKE ENERGY OHIO, INC.

____	Management policies, practices, and organization
____	Operating income
____	Rate Base
____	Allocations
____	Rate of return
____	Rates and tariffs
X	Other: Weather Normalization

July 20, 2012

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Attachments:

JM-1: Customer-class Econometric Model

JM-2: Actual Degree Days – Duke Energy Ohio

JM-3: Comparison to Duke Energy Ohio Ten-Year Normal

JM-4: Comparison to NOAA Thirty-Year Normal

I. INTRODUCTION AND PURPOSE

Q. PLEASE STATE YOUR NAME AND BUSINESS ADDRESS.

A. My name is Jose Merino, and my business address is 550 South Tryon Street, Charlotte, North Carolina, 28202.

Q. BY WHOM ARE YOU EMPLOYED AND IN WHAT CAPACITY?

A. I am employed by Duke Energy Business Services LLC (DEBS) as Director of Load Forecasting. DEBS provides various administrative and other services to Duke Energy Ohio, Inc., (Duke Energy Ohio or Company) and other affiliated companies of Duke Energy Corporation (Duke Energy).

Q. PLEASE BRIEFLY DESCRIBE YOUR EDUCATIONAL BACKGROUND AND PROFESSIONAL EXPERIENCE.

A. I received a Bachelor of Arts degree in Finance and Economics from Florida State University in August 1995. In May 2001, I received a Master's of Science degree in Management (MBA) from Georgia Institute of Technology in Atlanta, Georgia, with a specialization in Marketing and Finance. In December of 2010, I graduated from the University of North Carolina at Charlotte and obtained a Masters of Arts degree in Economics.

Between 1996 and 1999, I worked as a liquidity officer, a loan officer, and a financial planner for Diners Club in Ecuador. My primary job responsibilities included managing the company's cash position in local and foreign currencies, establishing lines of credit and originating loans for the industrial sector, overseeing the company's investment portfolio interest rate margin, and forecasting sales and revenues for credit card and loan products. I joined Duke

Energy in July 2001 as an MBA Commercial Associate in the Corporate Strategy department. After completing two years of rotational assignments in Charlotte, Houston, and Salt Lake City, I was offered a permanent position in the Corporate Risk organization as a Corporate Credit Manager. In this position, I was responsible for the implementation of a new corporate credit risk system, which included credit exposure, collateral support, and credit metrics reporting functionality. In 2004, I accepted a position in Duke Power Company, a subsidiary of Duke Energy, as Planning and Compliance Manager for the Bulk Power Marketing area. The main responsibilities for this role included revenue and costs projection, ownership of trade capture and risk management systems, and compliance with the mandates of different regulatory bodies regarding regulated trading operations. After Duke Energy merged with Cinergy Corp. in 2006, I moved to the Market Analytics group to supervise a team providing planning, marketing, and analytical support to Duke Energy's Economic and Business Development organizations. In 2008, I became Director, Wholesale and Commodities Business Support. This support function, which I supervised, was primarily accountable for projecting fuel consumption for Duke Energy's regulated generation fleet, forecasting revenues and costs for Duke's regulated portfolio optimization groups, and providing analytical support to wholesale origination. In October of 2010, I accepted my current position of Director, Load Forecasting.

Q. PLEASE SUMMARIZE YOUR RESPONSIBILITIES AS DIRECTOR, LOAD FORECASTING.

A. I am responsible for supervising the preparation of Duke Energy's operating companies' demand, energy, and customer forecasts, including the analysis and collection of forecast inputs, implementation of forecast systems and processes, and presentation of forecast results. I am also responsible for directing the development of analytical and business support to various organizations across Duke Energy, including Integrated Resource Planning, Financial Planning, Rates, Regulated Portfolio Optimization, and Corporate Strategy. Finally, I review the Duke Energy Ohio's load forecast methodology, assumptions, and technology used to ensure the Duke Energy's forecast processes are aligned with industry best practices.

Q. HAVE YOU PREVIOUSLY TESTIFIED BEFORE THE PUBLIC UTILITIES COMMISSION OF OHIO?

A. No.

Q. WHAT IS THE PURPOSE OF YOUR TESTIMONY IN THESE PROCEEDINGS?

A. My testimony explains the Company's process of weather normalizing Duke Energy Ohio's test period gas sales. In addition, my testimony discusses the "normal" weather data used to weather normalize the three-months actual gas sales for the test period. This same normal weather is also used to produce the nine-month forecast portion of the test period.

II. WEATHER NORMALIZATION OF DUKE ENERGY OHIO'S GAS SALES

Q. WHAT IS WEATHER NORMALIZATION?

A. Weather normalization is an adjustment of actual historical gas sales to estimate the impact of differences between actual weather and normal weather. The historical sales values are adjusted to what they would have been if normal weather had occurred. More detailed explanation of normal weather in included in Section III of my testimony.

Q. WHY DOES DUKE ENERGY OHIO WEATHER NORMALIZE ITS TEST PERIOD GAS SALES?

A. Duke Energy Ohio witness James A. Riddle explains why it is reasonable for the Company to weather normalize test period gas sales.

Q. DID YOU USE A GENERALLY ACCEPTED METHOD OF WEATHER NORMALIZING DUKE ENERGY OHIO'S GAS SALES FOR THE TEST PERIOD?

A. Yes. In general, the weather normalization of historical sales relies on a standard process that is used in all of Duke Energy's jurisdictions.

Q. HOW DID YOU WEATHER NORMALIZE DUKE ENERGY OHIO'S TEST PERIOD GAS SALES?

A. I will answer this question in two parts: first I will talk about the weather normalization of historical sales in the test period and then I will address the normalization of projected sales in the test period.

The starting point for the weather normalization of historical sales is determining the historical relationship between weather and energy usage. This relationship is quantified for each customer class by using econometric models and statistical techniques. Next, the difference between actual weather and normal weather is calculated. Once the relationship between weather and energy usage is established and the difference between actual weather and normal weather is calculated, actual historical gas sales are adjusted to reflect what they would have been under normal weather conditions.

Since normal weather is used to produce the nine-month forecast portion of the test period, by definition, these sales projections are weather normal. The specification of each customer-class econometric model is provided in Attachment JM-1.

Q. HOW DID YOU USE THESE ECONOMETRIC MODELS IN THE WEATHER NORMALIZATION PROCESS OF ACTUAL GAS SALES?

A. To weather normalize actual gas sales, I separated the econometric models into a weather component and a component dependent upon economic variables as follows:

(1) MCF = a + b*(E) + c*(P) + d*(HDDB) + e*(CDDB)

where:

MCF = Sales

E = Economic and other variables.

P = Energy Price

HDDB = Billing Heating Degree-days

CDDB = Billing Cooling Degree-days

a, b, c, d, = Equation Coefficients.

In the case of historical sales figures, actual sales resulted from actual weather conditions so equation (1) can be rewritten as:

(2) $MCF_{act} = a + b^*(E) + c^*(P) + d^*(HDDB_{act}) + e^*(CDDB_{act})$ with the "act" subscript referring to actual sales and actual weather conditions.

Similarly, under "normal" conditions, equation (1) would be:

(3) $MCF_{nml} = a + b^*(E) + c^*(P) + d^*(HDDB_{nml}) + e^*(CDDB_{nml})$ with the "nml" subscript referring to normal sales and weather conditions.

Subtracting equation (3) from equation (2) and simplifying yields:

$$(4)\ MCF_{nml} = MCF_{act} + d^*(HDDB_{nml} - HDDB_{act}) + e^*(CDDB_{nml} - CDDB_{act})$$

I derived the weather normal sales by scaling actual sales using a factor based on the weather coefficients in the econometric model equations. These equations are based on the econometric forecasting models as shown in Attachment JM-1. Note that only the coefficients on the weather variables, primarily heating and cooling degree days, are used in the weather normalization equations. The specification of each customer class weather normalizing equation is provided in Attachment JM-1.

III. NORMAL WEATHER

Q. WHAT IS A HEATING DEGREE DAY?

A. A Heating Degree Day (HDD) is calculated using a base temperature measured on the Fahrenheit scale and occurs when the daily average temperature is below the base. HDD measure the difference of the daily average temperature and the base temperature. The formula is:

Heating Degree Days = Base Temperature – Daily Average Temperature

Q. WHAT IS A COOLING DEGREE DAY?

A. A Cooling Degree Day (CDD) is also calculated using a base temperature measured on the Fahrenheit scale. However, it occurs when the daily average temperature is above the base. CDD measure the difference of the daily average temperature and the base temperature. The formula is:

Cooling Degree Days = Daily Average Temperature – Base Temperature

Q. WHAT HAS BEEN THE LONG-TERM TREND IN DEGREE DAYS?

A. For the years 1976 through 2011, HDD have experienced a downward trend. On the other hand, CDD have experienced a slight upward trend. The two graphs shown in Attachment JM-2 provide visual evidence of these trends.

Q. WHAT ARE THE ANNUAL NORMAL HEATING AND COOLING DEGREE DAYS?

A. The annual level of normal HDD is 4,902 and the annual level of normal CDD is 1,176 using a ten-year average methodology.

Q. PLEASE EXPLAIN "NORMAL" WEATHER.

A. Normal weather refers to expected weather conditions and is generally estimated by examining long-term trends. The long-term average for a particular weather variable will depend on the methodology and the length of history used. One must make a judgment about the weather conditions, or normal weather, expected to occur during the test period. The test period gas sales are based on such expected weather conditions.

More importantly, the "normal" weather must be representative of current weather trends. There is evidence of a downward trend in HDD while the trend in CDD is slightly upward.

Q. CAN YOU PLEASE DESCRIBE THE GENERAL APPROACH USED TO ESTIMATE THE ANNUAL NORMAL HEATING AND COOLING DEGREE DAYS?

I analyzed the actual hourly temperatures from National Oceanic and Atmospheric Administration (NOAA) for the year period between 2002 and 2011. Then I calculated the daily average temperatures and daily HDD and CDD and then totaled the results to obtain monthly degree days. Next, I calculated the averages by month over the ten-year period beginning in 2002 and ending in 2011.

Q. HOW DO THE ACTUAL ANNUAL HDD AND CDD FOR THE LAST TEN YEARS COMPARE TO THE NORMAL?

A. For 2002 through 2011, Duke Energy Ohio experienced five out of the ten years where actual annual HDD were below the ten-year normal of 4,902 and five out of ten years where actual annual HDD were above the ten-year normal of 4,902, an even distribution around the normal as one would expect, as shown in Attachment JM-3. For 2002 through 2011, Duke Energy Ohio experienced five out of the ten years where actual annual CDD were below the ten-year normal of 1,176 and five out of ten years where actual annual CDD were above the ten-year normal of 1,176, again an even distribution around the normal as shown in Attachment JM-3

Q. DID YOU MEASURE THE RELIABILITY OF THE NORMAL WEATHER?

A. Yes. One way to compare the relationship between the expected normal level of degree days to the actual number of degree days is to use a statistic known as the Mean Percent Error (MPE). MPE indicates whether the measure of normal degree days contains any bias to over-estimate or under-estimate the actual weather conditions. If MPE is close to zero, this indicates that there is no bias for the measure of normal to be different than the actual. The formula to calculate MPE is the sum of (Normal Degree Days minus Actual Degree Days) divided by Actual Degree Days. The sum is then divided by the number of observations. Mathematically:

$$\text{MPE} = \frac{1}{\text{N}}\sum_{t=1}^{N}\frac{\hat{Y}_t - Y_t}{Y_t}$$

Where $\hat{Y}$ = Normal Annual Degree Days

and Y = Actual Annual Degree Days

The MPE for HDD calculated for the years 2002 through 2011 comparing actual degree days to the ten-year average HDD used as normal results in an MPE of 1.6 percent. For CDD, the MPE is 1.7 percent. See Attachment JM-3. Both of these measures are reasonably small. These results indicate that the ten-year estimate of normal degree days is a reasonable predictor of HDD and CDD.

Q. DO YOU BELIEVE IT IS REASONABLE TO USE THE USE A TEN-YEAR WEATHER NORMALIZATION VERSUS A THIRTY-YEAR?

A. Yes. Based on the MPE approach previously described, the average MPE for the 2002-2011 period is lower for both heating and cooling degree days when the Duke Energy Ohio ten-year weather normal methodology is used as compared to NOAA's thirty-year weather normal.

Attachment JM-3 shows that the average MPE based on Duke Energy Ohio's ten- year normal calculation is 1.6 percent for HDD and 1.7 percent for CDD. Attachment JM-4 presents the same metrics using NOAA's thirty-year normal calculation: 3.2 percent for HDD and -2.8 percent for CDD.

Q. ARE OTHER MEASURES OF NORMAL WEATHER AVAILABLE?

A. Yes. The U.S. Department of Commerce, NOAA publishes measures of normal degree days. Additional information about NOAA is available at their website at www.noaa.gov.

Q. PLEASE EXPLAIN NOAA NORMALS.

A. NOAA is responsible for monitoring climate conditions in the United States. The standard time period prescribed by the United Nations World Meteorological Organization for measuring climate conditions is thirty years, and NOAA updates its calculations for the United States for these thirty-year periods at the end of each decade. The most current thirty-year period used by NOAA is 1981 through 2010. NOAA's next thirty-year normal weather period will be 1991 through 2020.

NOAA provides estimates of "normal" HDD and CDD using daily measurements obtained from the weather station located at the Northern Kentucky and Greater Cincinnati International Airport. These data are provided on a daily, monthly, and annual basis.

Q. WHAT ARE THE ANNUAL NORMAL HEATING AND COOLING DEGREE DAYS AS PROVIDED BY NOAA BASED FOR 1981 THROUGH 2010?

A. The annual level of normal HDD is 4,982 and the annual level of normal CDD is 1,124.

Q. HOW DO THE LAST TEN YEARS COMPARE TO NOAA NORMALS?

A. For 2002 through 2011, Duke Energy Ohio experienced eight out of ten years where actual annual HDD were below the NOAA normal of 4,982. On the CDD side, five out of the ten years were above the NOAA normal of 1,124 and five out of ten years were below the NOAA normal. This illustrates that, when the last ten years are considered, the NOAA HDD normal has been consistently higher than the actual number of HDD. However, for CDD, the distribution of actual values around the normal has been more even. This would be expected because the difference between the NOAA normal CDD of 1,124 and the Duke Energy Ohio normal CDD of 1,176 is smaller than the difference between the NOAA normal HDD of 4,982 and the Duke Energy Ohio normal HDD of 4,902.

Q. CAN THE DUKE ENERGY OHIO AND NOAA NORMAL WEATHER BE COMPARED USING MPE?

A. Yes. MPE can also indicate whether the measure of normal degree days contains any bias to over-estimate or under-estimate the actual weather conditions. For example, if MPE is positive, this indicates that there is a bias for the measure of normal to be higher than the actual.

The MPE for HDD calculated for the years 2002 through 2011 comparing actual degree days to the NOAA normal for the forecast results in an MPE of 3.2 percent. For CDD, the MPE is -2.8 percent. See Attachment JM-4. These measures indicate that the NOAA normal HDD has a bias to be higher than the actual, while NOAA normal CDD has a bias to be lower than the actual. Also, MPEs measuring NOAA normal HDD and CDD are both larger the MPE calculated using the Duke Energy Ohio normal weather.

Q. WHAT CAN YOU REASON FROM THESE RESULTS?

A. Given the evidence of a downward trend in HDD, a slight upward trend in CDD, and the fact that for the majority of recent years' HDD were below the NOAA normal, I concluded that the NOAA HDD normals are no longer representative. There is not enough of a difference in CDD normals to conclude an advantage. Therefore, the normals based on weather from 2002 through 2011, are, in my opinion, more accurate representations of normal weather.

IV. CONCLUSION

Q. WERE ATTACHMENTS JM-1 THROUGH JM-4 PREPARED BY YOU OR UNDER YOUR DIRECTION AND SUPERVISION?

A. Yes.

Q. IS THE INFORMATION CONTAINED IN ATTACHMENTS JM-1 THROUGH JM-4 ACCURATE TO THE BEST OF YOUR KNOWLEDGE AND BELIEF?

A. Yes.

Q. DOES THIS CONCLUDE YOUR PRE-FILED DIRECT TESTIMONY?

A. Yes.

Residential

Dependent Variable: LOG(MCFCUSRES_OH_KY_FT)
Method: Least Squares
Date: 03/09/12 Time: 09:20
Sample: 1981M01 2011M12
Included observations: 372
Convergence achieved after 9 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LRMPGRES_OH_KY_M(-2)	-0.143793	0.066209	-2.171827	0.0305
LRMPGRES_OH_KY_D(-2)	-0.051217	0.021820	-2.347198	0.0195
LRMPGRES_OH_KY_R(-2)	-0.090236	0.020435	-4.415820	0.0000
GASSATSH_OH_KY*HDDB_OH_KY_59_0_500	0.002393	9.89E-05	24.18535	0.0000
GASSATSH_OH_KY*HDDB_OH_KY_59_500	0.001038	4.42E-05	23.47637	0.0000
CDDB_OH_KY_65_0_100	-0.001922	0.000285	-6.741565	0.0000
CDDB_OH_KY_65_100	-0.000356	9.53E-05	-3.737649	0.0002
SPFH_GF_RP	-1.865792	0.296495	-6.292829	0.0000
@ISPERIOD("1987m6")	-0.152047	0.051211	-2.969032	0.0032
@ISPERIOD("2006m5")	-0.231601	0.051037	-4.537886	0.0000
@ISPERIOD("2007m10")	-0.192603	0.051517	-3.738670	0.0002
@ISPERIOD("2008m10")	-0.156221	0.051857	-3.012531	0.0028
@ISPERIOD("2010m5")	-0.207850	0.050522	-4.114051	0.0000
@MONTH=1	3.187148	0.258839	12.31325	0.0000
@MONTH=2	3.183338	0.258578	12.31095	0.0000
@MONTH=3	3.173535	0.257850	12.30769	0.0000
@MONTH=4	3.201834	0.255939	12.51015	0.0000
@MONTH=5	3.090772	0.255085	12.11662	0.0000
@MONTH=6	2.863941	0.256347	11.17213	0.0000
@MONTH=7	2.686671	0.257497	10.43380	0.0000
@MONTH=8	2.601464	0.257685	10.09551	0.0000
@MONTH=9	2.641471	0.257003	10.27799	0.0000
@MONTH=10	2.808632	0.255398	10.99710	0.0000
@MONTH=11	3.084840	0.255333	12.08165	0.0000
@MONTH=12	3.141854	0.258024	12.17660	0.0000
AR(1)	0.429593	0.049171	8.736641	0.0000

R-squared	0.996750	Mean dependent var	1.752702
Adjusted R-squared	0.996515	S.D. dependent var	0.910573
S.E. of regression	0.053752	Akaike info criterion	-2.941534
Sum squared resid	0.999698	Schwarz criterion	-2.667633
Log likelihood	573.1253	Hannan-Quinn criter.	-2.832760
Durbin-Watson stat	2.002506		

Inverted AR Roots	.43

Commercial Firm

Dependent Variable: LOG(MCFCOMF_OH_KY_FT)
Method: Least Squares
Date: 03/09/12 Time: 10:47
Sample: 1986M01 2011M12
Included observations: 312
Convergence achieved after 7 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(ECOM_OH_KY)	0.203770	0.029260	6.964131	0.0000
LOG(MPGCOM_OH_KY(-3)/CPI(-3))	-0.045381	0.016495	-2.751190	0.0063
HDDB_OH_KY_59_0_500	0.002146	9.72E-05	22.08105	0.0000
HDDB_OH_KY_59_500	0.000945	4.10E-05	23.03539	0.0000
CDDB_OH_KY_65_0_100	-0.000632	0.000265	-2.388877	0.0176
CDDB_OH_KY_65_100	-0.000381	8.24E-05	-4.625675	0.0000
1-D_2010PLUS	0.053796	0.013118	4.100778	0.0001
((@MONTH=10)+(@MONTH=11))*D_2005_2010	-0.112720	0.017428	-6.467720	0.0000
((@MONTH=4)+(@MONTH=5)+(@MONTH=6))*D_2005_2010	-0.076734	0.014817	-5.178599	0.0000
@ISPERIOD("1987m6")	-0.124756	0.046379	-2.689938	0.0076
@ISPERIOD("1993m10")	0.295912	0.047416	6.240706	0.0000
@ISPERIOD("1993m11")	-0.193917	0.046708	-4.151706	0.0000
@ISPERIOD("1996m04")	-0.194516	0.047754	-4.073266	0.0001
@ISPERIOD("1996m08")	0.148101	0.045749	3.237238	0.0014
@ISPERIOD("1997m4")	-0.201129	0.045556	-4.415002	0.0000
@ISPERIOD("2001m5")	-0.672036	0.047097	-14.26908	0.0000
@MONTH=1	12.40980	0.193862	64.01349	0.0000
@MONTH=2	12.41675	0.193629	64.12646	0.0000
@MONTH=3	12.39219	0.193244	64.12721	0.0000
@MONTH=4	12.43849	0.188337	66.04369	0.0000
@MONTH=5	12.30944	0.185710	66.28331	0.0000
@MONTH=6	12.11000	0.187809	64.48023	0.0000
@MONTH=7	11.98532	0.189349	63.29742	0.0000
@MONTH=8	11.91727	0.189550	62.87124	0.0000
@MONTH=9	11.94001	0.188888	63.21208	0.0000
@MONTH=10	12.08268	0.186739	64.70350	0.0000
@MONTH=11	12.32356	0.188129	65.50597	0.0000
@MONTH=12	12.35376	0.193602	63.81005	0.0000
AR(1)	0.197108	0.059772	3.297662	0.0011

R-squared	0.996914	Mean dependent var	14.03376
Adjusted R-squared	0.996608	S.D. dependent var	0.776711

S.E. of regression	0.045234	Akaike info criterion	-3.265601
Sum squared resid	0.579047	Schwarz criterion	-2.917694
Log likelihood	538.4338	Hannan-Quinn criter.	-3.126553
Durbin-Watson stat	2.008703		

Inverted AR Roots	.20

Commercial Interruptible

Dependent Variable: LOG(MCFCOMOP_OH_KY_TP)
Method: Least Squares
Date: 03/09/12 Time: 16:01
Sample: 1980M01 2011M12
Included observations: 384
Convergence achieved after 34 iterations
MA Backcast: *1979M11 1979M12*

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(ECOM_OH_KY)	1.088818	0.114528	9.506966	0.0000
WAPCOM_OH_KY(-4)/WPI0574(-4)	-0.013081	0.004945	-2.645415	0.0085
HDDB_OH_KY_59_0_500	0.000365	0.000126	2.907114	0.0039
HDDB_OH_KY_59_500	0.000287	5.79E-05	4.946156	0.0000
@ISPERIOD("1986m4")	-0.290259	0.069765	-4.160555	0.0000
@ISPERIOD("1986m10")	0.186629	0.073641	2.534308	0.0117
@ISPERIOD("1986m11")	-0.522588	0.073585	-7.101789	0.0000
@ISPERIOD("1987m3")	0.428437	0.069148	6.195916	0.0000
@ISPERIOD("1988m9")	-0.360311	0.069494	-5.184748	0.0000
@ISPERIOD("1988m12")	-0.331630	0.074054	-4.478207	0.0000
@ISPERIOD("1989m1")	0.205093	0.073893	2.775530	0.0058
@ISPERIOD("1995m5")	-0.412769	0.069079	-5.975350	0.0000
@ISPERIOD("1996m3")	-0.444893	0.069240	-6.425402	0.0000
@ISPERIOD("1996m11")	-1.227415	0.069429	-17.67858	0.0000
@ISPERIOD("2001m1")	-0.353913	0.080178	-4.414096	0.0000
@ISPERIOD("2001m2")	-1.353504	0.083015	-16.30429	0.0000
@ISPERIOD("2001m3")	-0.852368	0.080455	-10.59431	0.0000
@ISPERIOD("2003m4")	-0.345116	0.069782	-4.945642	0.0000
D_1965_1994	-0.243255	0.046002	-5.287893	0.0000
@YEAR=1987	-0.127069	0.052182	-2.435110	0.0154
@MONTH=1	5.115275	0.750700	6.814008	0.0000
@MONTH=2	5.137565	0.750441	6.846057	0.0000
@MONTH=3	5.091501	0.749600	6.792293	0.0000
@MONTH=4	5.066405	0.747106	6.781377	0.0000
@MONTH=5	4.901358	0.744921	6.579705	0.0000

@MONTH=6	4.784970	0.744549	6.426666	0.0000
@MONTH=7	4.709267	0.744598	6.324576	0.0000
@MONTH=8	4.722699	0.744790	6.340981	0.0000
@MONTH=9	4.735069	0.744959	6.356144	0.0000
@MONTH=10	4.759297	0.745614	6.383062	0.0000
@MONTH=11	4.904480	0.747555	6.560693	0.0000
@MONTH=12	5.017314	0.750790	6.682709	0.0000
AR(1)	0.600916	0.044845	13.39995	0.0000
MA(2)	0.226603	0.000147	1537.746	0.0000

R-squared	0.970175	Mean dependent var	11.73988
Adjusted R-squared	0.967363	S.D. dependent var	0.448826
S.E. of regression	0.081084	Akaike info criterion	-2.102290
Sum squared resid	2.301110	Schwarz criterion	-1.752494
Log likelihood	437.6398	Hannan-Quinn criter.	-1.963546
Durbin-Watson stat	1.972273		

Inverted AR Roots	.60

Industrial Firm

Dependent Variable: LOG(MCFINDFLA_OH_KY_FT)
Method: Least Squares
Date: 03/21/12 Time: 12:05
Sample (adjusted): 1979M05 2011M12
Included observations: 392 after adjustments
Convergence achieved after 7 iterations
MA Backcast: 1978M11 1979M04

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.414820	2.155976	-0.656232	0.5121
LOG(MPGIND_OH_KY(-3)/APEIND_OH_KY(-3))*(@MONTH=7)+(@MONTH=8)+(@MONTH=9)	-0.015359	0.003037	-5.056496	0.0000
HDDB_OH_KY_59_0_500	0.001335	4.98E-05	26.77703	0.0000
HDDB_OH_KY_59_500	0.000630	4.16E-05	15.13339	0.0000
@ISPERIOD("1981m5")	0.192012	0.075945	2.528295	0.0119
@ISPERIOD("1988m2")	0.315980	0.075922	4.161899	0.0000
@ISPERIOD("1995m6")	0.307378	0.076123	4.037931	0.0001
@ISPERIOD("2001m6")	-0.244244	0.076574	-3.189653	0.0015
@ISPERIOD("2006m2")	0.386850	0.087520	4.420111	0.0000
@ISPERIOD("2006m3")	-0.777559	0.087599	-8.876333	0.0000
@ISPERIOD("2001m11")	0.177963	0.076450	2.327820	0.0205
PDL01	0.022432	0.003210	6.988938	0.0000

PDL02	-0.015856	0.004037	-3.927754	0.0001
AR(1)	0.926407	0.020542	45.09772	0.0000
MA(6)	-0.182522	0.052820	-3.455566	0.0006

R-squared	0.977753	Mean dependent var	13.47107
Adjusted R-squared	0.976927	S.D. dependent var	0.691354
S.E. of regression	0.105016	Akaike info criterion	-1.631889
Sum squared resid	4.157714	Schwarz criterion	-1.479927
Log likelihood	334.8502	Hannan-Quinn criter.	-1.571662
F-statistic	1183.491	Durbin-Watson stat	2.004716
Prob(F-statistic)	0.000000		

Inverted AR Roots	.93			
Inverted MA Roots	.75	.38+.65i	.38-.65i	-.38-.65i
	-.38+.65i	-.75		

Lag Distribution of LOG(EM_OH_KY)	i	Coefficient	Std. Error	t-Statistic
. * |	0	0.02166	0.00310	6.98894
. * |	1	0.04177	0.00598	6.98894
. * |	2	0.06033	0.00863	6.98894
. * |	3	0.07735	0.01107	6.98894
. * |	4	0.09282	0.01328	6.98894
. * |	5	0.10674	0.01527	6.98894
. * |	6	0.11912	0.01704	6.98894
. * |	7	0.12995	0.01859	6.98894
. * |	8	0.13923	0.01992	6.98894
. * |	9	0.14697	0.02103	6.98894
. * |	10	0.15315	0.02191	6.98894
. * |	11	0.15779	0.02258	6.98894
. * |	12	0.16089	0.02302	6.98894
. * |	13	0.16244	0.02324	6.98894
. * |	14	0.16244	0.02324	6.98894
. * |	15	0.16089	0.02302	6.98894
. * |	16	0.15779	0.02258	6.98894
. * |	17	0.15315	0.02191	6.98894
. * |	18	0.14697	0.02103	6.98894
. * |	19	0.13923	0.01992	6.98894
. * |	20	0.12995	0.01859	6.98894
. * |	21	0.11912	0.01704	6.98894
. * |	22	0.10674	0.01527	6.98894
. * |	23	0.09282	0.01328	6.98894
. * |	24	0.07735	0.01107	6.98894
. * |	25	0.06033	0.00863	6.98894
. * |	26	0.04177	0.00598	6.98894

. * |	27	0.02166	0.00310	6.98894
	Sum of Lags	3.14042	0.44934	6.98894

Lag Distribution of LOG(MPGIND_OH_KY/WPI0574)	i	Coefficient	Std. Error	t-Statistic
* . |	0	-0.01472	0.00375	-3.92775
* . |	1	-0.02718	0.00692	-3.92775
* . |	2	-0.03737	0.00952	-3.92775
* . |	3	-0.04530	0.01153	-3.92775
* . |	4	-0.05096	0.01298	-3.92775
* . |	5	-0.05436	0.01384	-3.92775
* . |	6	-0.05549	0.01413	-3.92775
* . |	7	-0.05436	0.01384	-3.92775
* . |	8	-0.05096	0.01298	-3.92775
* . |	9	-0.04530	0.01153	-3.92775
* . |	10	-0.03737	0.00952	-3.92775
* . |	11	-0.02718	0.00692	-3.92775
* . |	12	-0.01472	0.00375	-3.92775
	Sum of Lags	-0.51531	0.13120	-3.92775

Industrial Interruptible

Dependent Variable: LOG(MCFINDOP_OH_KY_TP)
Method: Least Squares
Date: 03/12/12 Time: 21:56
Sample: 1999M01 2011M12
Included observations: 156
Convergence achieved after 5 iterations
MA Backcast: 1998M01 1998M12

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	13.56285	0.095796	141.5801	0.0000
EM_OH_KY	0.005631	0.000642	8.774553	0.0000
LOG(JQIND_OH_KY_GAS(-3))	0.524343	0.168277	3.115951	0.0022
HDDB_OH_KY_59	0.000255	2.04E-05	12.50218	0.0000
D_M678	-0.037994	0.016053	-2.366719	0.0193
@YEAR=2006	0.072241	0.014786	4.885791	0.0000
@ISPERIOD("2002m2")	-0.337181	0.048319	-6.978170	0.0000
@ISPERIOD("2011m10")	-0.159456	0.054380	-2.932239	0.0039
PDL01	-0.013744	0.001231	-11.16515	0.0000
MA(12)	0.435592	0.074844	5.819963	0.0000

R-squared	0.904986	Mean dependent var	14.06600
Adjusted R-squared	0.899129	S.D. dependent var	0.166643
S.E. of regression	0.052926	Akaike info criterion	-2.977890
Sum squared resid	0.408969	Schwarz criterion	-2.782386
Log likelihood	242.2754	Hannan-Quinn criter.	-2.898485
F-statistic	154.5132	Durbin-Watson stat	1.988136
Prob(F-statistic)	0.000000		

Inverted MA Roots	.90+.24i	.90-.24i	.66-.66i	.66+.66i
	.24+.90i	.24-.90i	-.24+.90i	-.24-.90i
	-.66+.66i	-.66+.66i	-.90-.24i	-.90+.24i

Lag Distribution of LOG(WAPIND_OH_KY/CPI)	i	Coefficient	Std. Error	t-Statistic
* . |	0	-0.02577	0.00231	-11.1651
* . |	1	-0.02405	0.00215	-11.1651
* . |	2	-0.02233	0.00200	-11.1651
* . |	3	-0.02062	0.00185	-11.1651
* . |	4	-0.01890	0.00169	-11.1651
* . |	5	-0.01718	0.00154	-11.1651
* . |	6	-0.01546	0.00138	-11.1651
* . |	7	-0.01374	0.00123	-11.1651
* . |	8	-0.01203	0.00108	-11.1651
* . |	9	-0.01031	0.00092	-11.1651
* . |	10	-0.00859	0.00077	-11.1651
* . |	11	-0.00687	0.00062	-11.1651
* . |	12	-0.00515	0.00046	-11.1651
* . |	13	-0.00344	0.00031	-11.1651
* . |	14	-0.00172	0.00015	-11.1651
	Sum of Lags	-0.20616	0.01846	-11.1651

Governmental

Dependent Variable: LOG(MCFOPA_OH_KY_TP_FT)
Method: Least Squares
Date: 03/12/12 Time: 23:12
Sample (adjusted): 1977M06 2011M12
Included observations: 415 after adjustments
Convergence achieved after 8 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.

LOG(E90X_OH_KY(-4))	1.884055	0.312123	6.036255	0.0000
LOG(MPGOPA_OH_KY/CPI)*D_M678	-0.309252	0.078818	-3.923645	0.0001
LOG(MPGOPA_OH_KY(-4)/CPI(-4))*(1-D_M678)	-0.250075	0.069506	-3.597885	0.0004
HDDB_OH_KY_59_0_500	0.001676	0.000134	12.49913	0.0000
HDDB_OH_KY_59_500	0.000731	5.89E-05	12.41511	0.0000
@ISPERIOD("1977m8")	0.476504	0.074794	6.370885	0.0000
@ISPERIOD("1978m8")	-0.235702	0.074804	-3.150939	0.0018
@ISPERIOD("1980m7")	-0.249419	0.074770	-3.335810	0.0009
@ISPERIOD("1981m9")	-0.251943	0.074784	-3.368961	0.0008
@ISPERIOD("1982m11")+@ISPERIOD("1982m12")	0.162903	0.074491	2.186886	0.0294
@ISPERIOD("1993m6")	0.221689	0.075288	2.944561	0.0034
@ISPERIOD("1996m5")+@ISPERIOD("1996m6")	0.224990	0.074631	3.014703	0.0027
@ISPERIOD("1999m6")	0.646898	0.075120	8.611516	0.0000
@ISPERIOD("2003m12")	-0.203666	0.075021	-2.714795	0.0069
@ISPERIOD("2008m9")	-0.254513	0.076579	-3.323536	0.0010
@ISPERIOD("2010m6")	0.215363	0.086173	2.499196	0.0129
@ISPERIOD("2010m7")	-0.275396	0.085956	-3.203929	0.0015
@ISPERIOD("2011m8")+@ISPERIOD("2011m9")	0.208658	0.074313	2.807839	0.0052
@MONTH=1	3.862326	1.488267	2.595183	0.0098
@MONTH=2	3.852665	1.488194	2.588818	0.0100
@MONTH=3	3.822371	1.488000	2.568798	0.0106
@MONTH=4	3.813092	1.486637	2.564911	0.0107
@MONTH=5	3.688106	1.485531	2.482685	0.0135
@MONTH=6	3.586771	1.484927	2.415452	0.0162
@MONTH=7	3.527279	1.484808	2.375579	0.0180
@MONTH=8	3.496622	1.484799	2.354947	0.0190
@MONTH=9	3.461372	1.484435	2.331778	0.0202
@MONTH=10	3.572461	1.484887	2.405881	0.0166
@MONTH=11	3.752525	1.486141	2.525013	0.0120
@MONTH=12	3.790841	1.488016	2.547581	0.0112
AR(1)	0.850371	0.026656	31.90149	0.0000

R-squared	0.979672	Mean dependent var	12.67537
Adjusted R-squared	0.978084	S.D. dependent var	0.652589
S.E. of regression	0.096610	Akaike info criterion	-1.764503
Sum squared resid	3.584077	Schwarz criterion	-1.463595
Log likelihood	397.1343	Hannan-Quinn criter.	-1.645513
Durbin-Watson stat	2.051162		

Inverted AR Roots	.85

Residential

WN_MCFRESF_OH_KY_FT = MCFRESF_OH_KY_FT*EXP(0.00239262626761*GASSATSH_OH_KY*(HDDBN_OH_KY_59_0_500-HDDB_OH_KY_59_0_500) + 0.00103774437279*GASSATSH_OH_KY*(HDDBN_OH_KY_59_500-HDDB_OH_KY_59_500)-0.00192249233941*(CDDBN_OH_KY_65_0_100-CDDB_OH_KY_65_0_100)- 0.000356162680704*(CDDBN_OH_KY_65_100-CDDB_OH_KY_65_100))

Commercial Firm

WN_MCFCOMF_OH_KY_FT = MCFCOMF_OH_KY_FT*EXP(0.0021461101352*(HDDBN_OH_KY_59_0_500-HDDB_OH_KY_59_0_500) + 0.000944553773709*(HDDBN_OH_KY_59_500-HDDB_OH_KY_59_500)- 0.000632039459426*(CDDBN_OH_KY_65_0_100-CDDB_OH_KY_65_0_100) - 0.000381254204367*(CDDBN_OH_KY_65_100-CDDB_OH_KY_65_100))

Commercial Interruptible

WN_MCFCOMOP_OH_KY_TP =MCFCOMOP_OH_KY_TP*EXP(0.000364985660561*(HDDBN_OH_KY_59_0_500-HDDB_OH_KY_59_0_500) + 0.000286555760064*(HDDBN_OH_KY_59_500-HDDB_OH_KY_59_500))

Industrial Firm

WN_MCFINDFLA_OH_KY_FT = MCFINDFLA_OH_KY_FT*EXP(0.0013347995477*(HDDBN_OH_KY_59_0_500-HDDB_OH_KY_59_0_500) + 0.000629620639205*(HDDBN_OH_KY_59_500-HDDB_OH_KY_59_500))

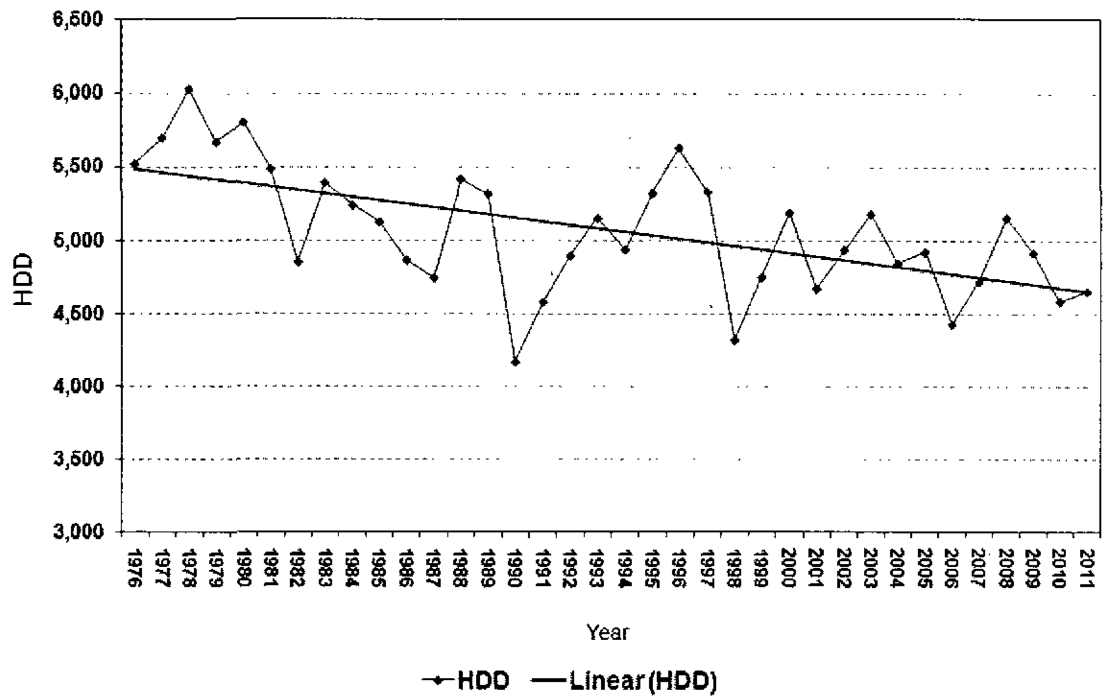
Industrial Interruptible

WN_MCFINDOP_OH_KY_TP = MCFINDOP_OH_KY_TP*EXP(0.000254938577097*(HDDBN_OH_KY_59-HDDB_OH_KY_59))

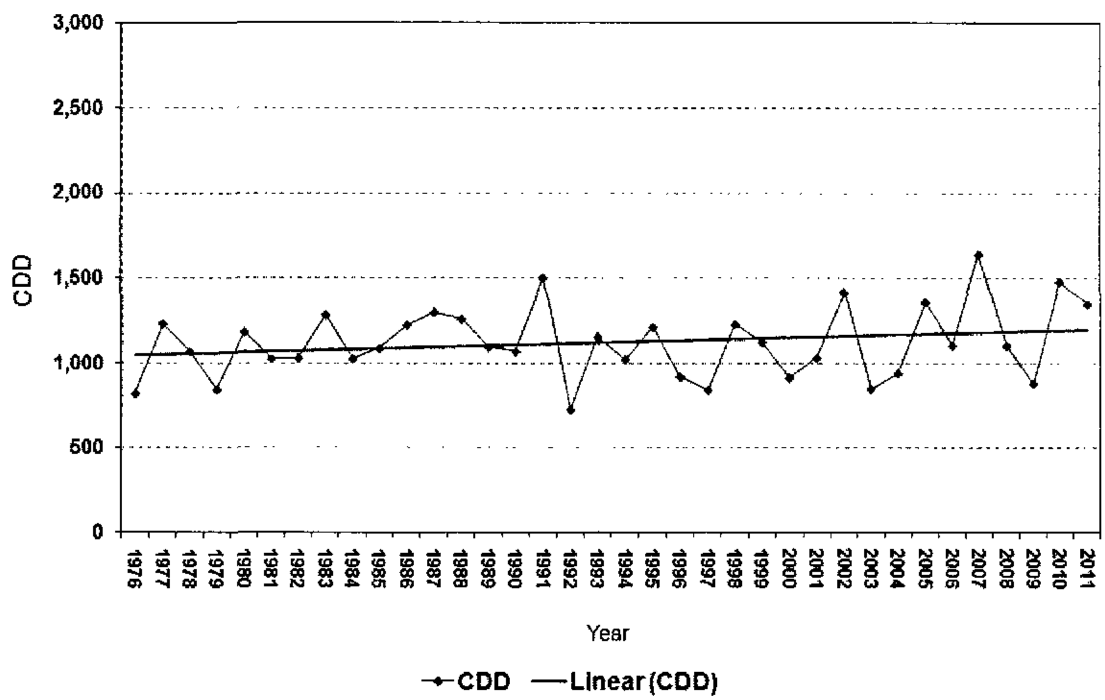
Governmental

WN_MCFOPA_OH_KY_TP_FT = MCFOPA_OH_KY_TP_FT*EXP(0.00167601242159*(HDDBN_OH_KY_59_0_500-HDDB_OH_KY_59_0_500) + 0.000731218268441*(HDDBN_OH_KY_59_500-HDDB_OH_KY_59_500

Actual Heating Degree Days (HDD) - Duke Energy Ohio



Actual Cooling Degree Days (CDD) - Duke Energy Ohio



Comparison of Actual HDD to Duke Energy Ohio 10 Year Normal

	Actual HDD	Normal HDD	Normal vs. Actual	MPE
2002	4,938	4,902	Below	-0.7%
2003	5,180	4,902	Below	-5.4%
2004	4,847	4,902	Above	1.1%
2005	4,925	4,902	Below	-0.5%
2006	4,430	4,902	Above	10.7%
2007	4,723	4,902	Above	3.8%
2008	5,155	4,902	Below	-4.9%
2009	4,919	4,902	Below	-0.3%
2010	4,587	4,902	Above	6.9%
2011	4,656	4,902	Above	5.3%
Mean Percentage Error (MPE)				**1.6%**

Comparison of Actual CDD to Duke Energy Ohio 10 Year Normal

	Actual CDD	Normal CDD	Normal vs. Actual	MPE
2002	1,417	1,176	Below	-17.0%
2003	849	1,176	Above	38.5%
2004	941	1,176	Above	25.0%
2005	1,361	1,176	Below	-13.6%
2006	1,105	1,176	Above	6.4%
2007	1,645	1,176	Below	-28.5%
2008	1,106	1,176	Above	6.3%
2009	881	1,176	Above	33.5%
2010	1,481	1,176	Below	-20.6%
2011	1,349	1,176	Below	-12.8%
Mean Percentage Error (MPE)				**1.7%**

Comparison of Actual HDD to NOAA 30 Year Normal

	Actual HDD	Normal CDD	Normal vs. Actual	MPE
2002	4,938	4,982	Above	0.9%
2003	5,180	4,982	Below	-3.8%
2004	4,847	4,982	Above	2.8%
2005	4,925	4,982	Above	1.2%
2006	4,430	4,982	Above	12.5%
2007	4,723	4,982	Above	5.5%
2008	5,155	4,982	Below	-3.4%
2009	4,919	4,982	Above	1.3%
2010	4,587	4,982	Above	8.6%
2011	4,656	4,982	Above	7.0%
Mean Percentage Error (MPE)				**3.2%**

Comparison of Actual CDD to NOAA 30 Year Normal

	Actual HDD	Normal CDD	Normal vs. Actual	MPE
2002	1,417	1,124	Below	-20.7%
2003	849	1,124	Above	32.4%
2004	941	1,124	Above	19.4%
2005	1,361	1,124	Below	-17.4%
2006	1,105	1,124	Above	1.7%
2007	1,645	1,124	Below	-31.7%
2008	1,106	1,124	Above	1.6%
2009	881	1,124	Above	27.6%
2010	1,481	1,124	Below	-24.1%
2011	1,349	1,124	Below	-16.7%
Mean Percentage Error (MPE)				**-2.8%**