NORTHWEST POWER AND CONSERVATION COUNCIL

RPM Technical Appendix

DRAFT

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1/30/2015

Contents

1 RPM FUTURE DISTRIBUTION SIMULATION

RPM uses several statistical modeling approaches to generate a distribution of forecast time series from a set of reference forecasts. The distribution of forecasts is then used to assess the risk of different potential "futures".

Note: this document is intended to act as a compact reference for the RPM dispatch methodology. To get a much more exhaustive description of the methodology and the intent see appendices L and P in the 5th Power Plan.

1.1 RISK MODELS

1.1.1 RPM Load Risk Model

The RPM load model modifies a reference forecast that is input into the model. Let $d_{Flat}(t)$ be the forecast for flat (aMW) electric load at time (or period) t. Then the forecast for future or game i is modified by three terms. The first is

$$P_{t,i} = e^{\alpha_F \varepsilon_{F,i} + {}^{\alpha_L}/_{20} * \varepsilon_{L,i}(y_t - y_0) + {}^{\alpha_Q}/_{20^2} * \varepsilon_{Q,i}(y_t - y_0)^2}$$

where $y_t = year\ at\ time\ t$; α_F, α_L and α_Q are parameters; and $\varepsilon_{F,i} \sim \varepsilon_{L,i} \sim \varepsilon_{Q,i} \sim N(0,1)$, that is they are independent standard normal random variables. The second is

$$S_{t,i} = e^{I_{\{q_t = 1\ or\ 3\}} \tau_{q_t,i}}$$

where $I_{\{\ \}}$ is the indicator or identity function and $q_t = quarter\ at\ time\ t$ and $\tau_{q_t,i} \sim N(0,.05)$ is a normal random variable. The third is

$$J_{t,i} = e^{I_{\{\beta_i < y_t - y_0 < \beta_i + \omega_i\}} \xi_i - I_{\{\beta_i + \omega_i < y_t - y_0 < \beta_i + \omega_i + e^{\xi_i}\}} \xi_i / \gamma}$$

where $\beta_i \sim Unif(0, 21.25)$ and $\omega_i \sim Unif(2, 5)$ and $\xi_i \sim Unif(-.1, .08)$ and γ is a scaling factor. Given these three terms, the load risk for future i at time t, $D_{Flat}(t,i)$ is

$$D_{Flat}(t,i) = P_{t,i} * S_{t,i} * J_{t,i} * d_{Flat}(t)$$

Similarly the reference forecast for the weather-normalized load $d_{WN}(t)$ at time t for future i is modified as

$$D_{WN}(t,i) = P_{t,i} * S_{t,i} * J_{t,i} * d_{WN}(t)$$

The values used in the 6th plan for the parameters in this model were $\alpha_F = 0$, $\alpha_L = \frac{.2}{20} * .3$, $\alpha_Q = 0$ and $\gamma = 1$.

1.1.2 RPM Natural Gas Price Risk Model

The RPM natural gas price model modifies a reference forecast that in input into the model. Let $g(t)$ be the forecast at time t. The forecast for future i is modified by three terms. The first is

$$P_{t,i} = e^{\alpha_F \theta_{F,i} + \alpha_L \theta_{L,i}(y_t - y_0) + \alpha_Q \theta_{Q,i}(y_t - y_0)^2}$$

where $y_t = year\ at\ time\ t$; α_F, α_L and α_Q are parameters; and $\theta_{F,i} \sim \theta_{L,i} \sim \theta_{Q,i} \sim Triangular(-1,0,1)$, that is they are independent triangular random variables. The second is

$$S_{t,i} = e^{I_{\{q_{t=2\ or\ 4}\}} \tau_{t,i}}$$

where $I_{\{\ \}}$ is the indicator or identity function and $q_t = quarter\ at\ time\ t$ and $\tau_{t,i} \sim N(0,.3)$ is a normal random variable. The third takes several factors that define start and end times where a "jump" factor is applied. For the factors take

$$\phi_{s,1} = \beta_{i,1}$$

$$\phi_{d,1} = \frac{\eta_{i,1}}{\omega_{i,1}}$$

$$\phi_{r,1} = \frac{\eta_{i,1}}{\omega_{i,1}} e^{\omega_{i,1}}$$

$$\phi_{s,2} = \phi_{s,1} + \phi_{d,1} + \phi_{r,1} + \beta_{i,2}$$

$$\phi_{d,2} = \frac{\eta_{i,2}}{\omega_{i,2}}$$

$$\phi_{r,2} = \frac{\eta_{i,2}}{\omega_{i,2}} e^{\omega_{i,2}}$$

Then the third term is given by

$$J_{t,i} = \prod_j e^{I_{\{\phi_{s,j} < y_t - y_0 < \phi_{s,j} + \phi_{d,j}\}} {}^{\omega_{i,j}} - I_{\{\phi_{s,j} + \phi_{d,j} < y_t - y_0 < \phi_{s,j} + \phi_{d,j} + \phi_{r,j}\}} {}^{\omega_{i,j}/\gamma_j}}$$

Where $\eta_{i,j}$ are parameters, $\beta_{i,1} \sim Unif(0, 7.5)$, $\beta_{i,2} \sim Unif(1, 5)$, and $\omega_{i,j} \sim Unif(0, .7)$ and γ_j are scaling factors. Given these three terms, the natural gas price for future i at time t is

$$G(t, i) = P_{t,i} * S_{t,i} * J_{t,i} * g(t)$$

The values used in the sixth plan for these parameters were $\alpha_F = .175$, $\alpha_L = .98$, $\alpha_Q = .8$, $\eta_{i,1} = \eta_{i,2} = .75$ and $\gamma_1 = \gamma_2 = 10$

1.1.3 RPM Carbon Tax Risk Model

The RPM carbon tax risk model uses a few parameters to estimate a CO2 tax for the model.

$$C(t,i) = I_{\{t>s_i\}} * min\left(1, u_i * {}^{s_i}/_{l}\right) * q$$

where $s_i \sim LogN(18, 16)$ represents the first period in which the tax is applied and $u_i \sim Unif(0,1)$ and q and l are parameters.

In the 6th plan, $q = 100$ and $l = 14.24$.

1.1.4 RPM Electricity Price Risk Model

The RPM electricity price model modifies a reference forecast that in input into the model. Let $m_{On}(t)$ be the on-peak electricity price forecast and $m_{Off}(t)$ be the off-peak electricity price forecast at time t. The forecast for future i is modified by two terms. The first is

$$P_{t,i} = e^{\alpha_F \theta_{F,i} + \alpha_L \theta_{L,i}(y_t - y_0) + \alpha_Q \theta_{Q,i}(y_t - y_0)^2}$$

where $y_t = year\ at\ time\ t$; α_F, α_L and α_Q are parameters; and $\theta_{F,i} \sim \theta_{L,i} \sim \theta_{Q,i} \sim Triangular(-1,0,1)$, that is they are independent triangular random variables. The second takes several factors that define start and end times where a "jump" factor is applied. For the factors take

$$\phi_{s,1} = \beta_{i,1}$$

$$\phi_{d,1} = \frac{\eta_{i,1}}{\omega_{i,1}}$$

$$\phi_{r,1} = \frac{\eta_{i,1}}{\omega_{i,1}} e^{\omega_{i,1}}$$

$$\phi_{s,2} = \phi_{s,1} + \phi_{d,1} + \phi_{r,1} + \beta_{i,2}$$

$$\phi_{d,2} = \frac{\eta_{i,2}}{\omega_{i,2}}$$

$$\phi_{r,2} = \frac{\eta_{i,2}}{\omega_{i,2}} e^{\omega_{i,2}}$$

Then the second term is given by

$$J_{t,i} = \prod_j e^{I_{\{\phi_{s,j} < y_t - y_0 < \phi_{s,j} + \phi_{d,j}\}} \omega_{i,j} - I_{\{\phi_{s,j} + \phi_{d,j} < y_t - y_0 < \phi_{s,j} + \phi_{d,j} + \phi_{r,j}\}} \omega_{i,j}/\gamma_j}$$

Where $\eta_{i,j}$ are parameters, $\beta_{i,1} \sim Unif(0, 20)$, $\beta_{i,2} \sim Unif(4, 9)$, and $\omega_{i,j} \sim Unif(0,2.5)$ and γ_j are scaling factors.

The third term scales the distribution according to the forecasts of gas g_t, load d_t and hydro h_t. It also uses a systematic sampling of hydro $H_{t,i}$ as well as the risk model outputs for the natural gas price $G_{t,i}$ and the load $D_{t,i}$.

$$B_{t,i} = \frac{G_{t,i}{}^{\rho_1}\, e^{\rho_2 D_{t,i} + \rho_3 H_{t,i}}}{g_t{}^{\rho_1}\, e^{\rho_2 d_t + \rho_3 h_t}}$$

Where ρ_i are parameters. Given these three terms and the carbon tax price $C(t, i)$, the on-peak electricity price for the east zone for future i at time t is

$$M_{On}(t, i) = P_{t,i} * B_{t,i} * J_{t,i} * m_{On}(t) + C(t, i) * \frac{k}{2000}$$

and the off-peak electricity price for the east zone for future i at time t is

$$M_{Off}(t, i) = P_{t,i} * B_{t,i} * J_{t,i} * m_{Off}(t) + C(t, i) * \frac{k}{2000}$$

where k is a parameter representing the CO2 emissions associated with market power.

The values used in the sixth plan for these parameters were $\alpha_F = .175$, $\alpha_L = .98$, $\alpha_Q = .8$, $\eta_{i,1} = \eta_{i,2} = 3$, $\gamma_1 = \gamma_2 = 10$, $\rho_1 = .44$, $\rho_2 = .0000438$, $\rho_3 = -.0000134$ and $k = 1053$

1.1.5 RPM REC Risk Model

The RPM REC risk model modifies a reference forecast that is input into the model. It is similar to the other risk models. The forecast, r_t, for future i is modified by two terms. The first is

$$P_{t,i} = e^{\alpha_F \varepsilon_{F,i} + \alpha_L \varepsilon_{L,i}(y_t - y_0) + \alpha_Q \varepsilon_{Q,i}(y_t - y_0)^2}$$

where $y_t = year\ at\ time\ t$; α_F, α_L and α_Q are parameters; and $\varepsilon_{F,i} \sim \varepsilon_{L,i} \sim \varepsilon_{Q,i} \sim N(0, .15)$, that is they are independent normal random variables. The second is

$$S_{t,i} = e^{\tau_{t,i}}$$

where $\tau_{t,i} \sim N(0,.15)$ is a normal random variable. Given these two terms, the REC price for future i at time t, $R_{t,i}$, is

$$R_{t,i} = P_{t,i} * S_{t,i} * m_t$$

The values used in the 6th plan for the parameters in this model were $\alpha_F = .3$, $\alpha_L = 0$ and $\alpha_Q = 0$.

1.1.6 RPM PTC Risk Model

The RPM PTC risk model uses a few parameters and modifies the carbon tax risk model. That is, given a baseline PTC of b the PTC for future i at time t is

$$B(t,i) = \left[I_{\{C(t,i)<b*k\}} b + I_{\{b*k<C(t,i)<b*j\}}\big(b*j - C(t,i)\big)\right] * I_{\{t<p\}}$$

where k and j are parameters and $p \sim Triangular(0,20,85)$.

In the 6th plan the value for the parameters were $b = 9.9$, $k = .5$ and $j = 1.5$.

1.2 FUTURES FUNCTIONS

1.2.1 Load

With the above risk model there are four risk-informed load time series that are calculated for use in RPM. The flat electric load forecast and the weather normalized load forecast both for on-peak and off-peak periods.

The flat electric on-peak load at time t for future i for is

$$D_{Flat,On}(t,i) = D_{Flat}(t,i) * k_{On}(t)$$

where $k_{On}(t)$ is a forecast multiplier based on the ratio of the on-peak load to the flat load. Similarly the flat electric off-peak load at time t for future i is

$$D_{Flat,Off}(t,i) = D_{Flat}(t,i) * k_{Off}(t)$$

where $k_{Off}(t)$ is a forecast multiplier based on the ratio of the off-peak load to the flat load.

The weather-normalized on-peak load at time t for future i is

$$D_{WN,On}(t,i) = D_{WN}(t,i) * k_{On}(t)$$

and the weather-normalized off-peak load at time t for future i is

$$D_{WN,On}(t,i) = D_{WN}(t,i) * k_{Off}(t)$$

1.2.2 Natural Gas

With the above risk model there are two risk-informed natural gas time series that are calculated for use in the RPM. The natural gas prices for the west zone and the natural gas prices for the east zone. The price for the west zone is simply the price calculated by the risk model that is

$$G_W(t,i) = G(t,i)$$

The price for the east zone is

$$G_E(t,i) = \max(v, G(t,i) - u(t))$$

where v is a parameter representing the minimum price for natural gas and $u(t)$ is a forecast of the difference in price between the east and the west zones.

1.2.3 Electricity Price

With the above risk model there are four risk-informed electricity market price time series. Two are from the east zone and are given above, that is for on-peak

$$M_{East,On}(t,i) = M_{On}(t,i)$$

And for off-peak in the east zone

$$M_{East,Off}(t,i) = M_{Off}(t,i)$$

For the west zone there is an adder for both on-peak and off-peak, $W_{On}(t)$ and $W_{Off}(t)$ respectively. That is, for the west zone the on-peak electricity price is

$$M_{West,On}(t,i) = M_{On}(t,i) + W_{On}(t)$$

And for the west zone the off-peak electricity price is

$$M_{West,Off}(t,i) = M_{Off}(t,i) + W_{Off}(t)$$

1.2.4 Hydro Generation

The hydro generation time series is a function of the 80 water years. RPM is setup to select a random water year and then proceed sequentially from that water year through the 20 year run time. That is, if $h_{West,On}(q)$ is the hydro generation for quarter q of the historic record, $1 \leq q \ \leq 80 * 4$ for the 80 water years. And $h_{West,Off}(q)$, $h_{East,On}(q)$ and $h_{East,Off}(q)$ are defined similarly, then the time series for on-peak hydro generation for future i at time t is

$$H_{West,On}(t,i) = h_{West,On}(j+t)$$

where $j \sim DiscreteUnif(1{,}80 * 4 - 3)$. Similarly

$$H_{West,Off}(t,i) = h_{West,Off}(j+t)$$

$$H_{East,On}(t,i) = h_{East,On}(j+t)$$

$$H_{East,Off}(t,i) = h_{East,Off}(j+t)$$

2 ESTIMATING PARAMETERS FOR RPM

RPM has many parameters that drive the model results as well as inputs. These parameters are based on a variety of sources including forecasts, historic data and expert input. This section documents the process of estimating these parameters.

2.1 LOAD MODEL

The primary component used for scaling the load model is of the form

$$P_{t,i} = e^{\alpha_F \varepsilon_{F,i} + {\alpha_L}/{20} * \varepsilon_{L,i}(y_t - y_0) + {\alpha_Q}/{20^2} * \varepsilon_{Q,i}(y_t - y_0)^2}$$

If you consider that the random variables $\varepsilon_{F,i} \sim \varepsilon_{L,i} \sim \varepsilon_{Q,i} \sim N(0,1)$ do not depend on time then this equation can be seen as only depending on time through the year of the simulation. The load forecast for the 7th plan has a high, medium and low forecast. To get this risk model to have a spread based on that forecast, regression is used. That is, if H_t, M_t and L_t are the high, medium and low load forecasts respective then use regression to find a, b and c in

$$\ln(H_t/M_t) = a + b(y_t - y_0) + c(y_t - y_0)^2 + \epsilon$$

Use the same procedure for $\ln(L_t/M_t)$. This can be done as if the random variables are fixed values because they do not depend on time. Take an average or weighted average of the variables to get a single parameter because the model assumes log-symmetry. The problem is how to alter these values to give the desired range.

While it may be possible to use a more complicated model with multiplicative errors, the easier thing is to recognize that in simple regression there is normally error around the estimation of the coefficients. If we assume that the distribution for b has zero expectation, we can take the value from the regression to be a measure of the spread. Now since $\varepsilon_{L,i} \sim N(0,1)$

$$\alpha_L/_{20} * \varepsilon_{L,i} \sim N\left(0, \alpha_L/_{20}\right)$$

We want a value where the probability of exceeding it is .85, which is the probability associated with the high load forecast. Since we have normality

$$\Pr\left[\alpha_L/_{20} * \varepsilon_{L,i} < \alpha_L/_{20} * z_{.85}\right] = .85$$

Thus we set

$$b = \alpha_L/_{20} * z_{.85}$$

Which implies

$$\alpha_L = 20b/_{z_{.85}}$$

So taking b from the regression above it is possible to construct an estimate for α_L with a specified probability of exceeding a range.

The same method applies to the values for a and c above. This allows for RPM to be directly tied to the range implied by the load forecast.

The seasonal component adds some variability based on the quarter. The factor only depends on the quarter since it is of the form

$$S_{t,i} = e^{\tau_{q_t,i}}$$

The best way to accomplish this is to estimate seasonality based on the historic volatility. Because of the DSIs we need to adjust history to avoid carrying forward volatility that would not occur in the future. If we assume the seasonal factor is not intended to shape, then we know the expectation for each quarter should be zero. Thus

$$\ln(S_{t,i}) \quad = \tau_{q_t,i}$$

where is a normal distribution with zero expectation. So taking the adjusted history first normalize each quarter by the annual average and then normalize the resulting shapes by the average quarterly shape. That creates a sample similar to $S_{t,i}$ which can be used to estimate the standard deviation for each quarter.