Strategic Energy Management Modeling: What's good enough?

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Abstract:

Both commercial and industrial Strategic Energy Management (SEM) programs include the development of one or more models of energy consumption for each participating site. Protocols for model design have been put forward with many specifics on model requirements. Significant resources are often spent on developing models due to data and specification requirements. The question of what level of model development is good enough to estimate program level savings has not been addressed.

Energy Trust of Oregon has been implementing SEM for commercial and industrial customers for many years, and many hundreds of models have been developed. This study selects a sample of gas and electric models from the industrial SEM program, and reruns them using standardized simplified specifications. The overall savings estimated by the models specified by the program and those from the simplified models were compared, to determine if the difference in savings estimated by the two methods is statistically significant. The results prove useful in guiding programs on what level of analysis should be undertaken for SEM participants at the start of an SEM engagement. As simplified models rely on a reduced set of variables and data, the results of this study also provide guidance on what types of data the program should collect to develop the initial model.

Background and Introduction

Strategic Energy Management (SEM) programs have expanded over the years in the United States and abroad (CEE 2016). SEM programs vary widely in implementation and scope, but typically involve a longer-term customer engagement to train and embed energy efficient practices. Over the years, the SEM industry has developed a set of defining minimum elements that set the baseline for SEM (BPA 2015). Monitoring and program performance is one of these elements. This element requires the "regular analysis of actual performance against modeled performance". This has typically entailed the development of one or more energy models for each SEM participant that "capture all key factors that influence energy consumption and production".

Energy Trust of Oregon (Energy Trust) has been implementing industrial Strategic Energy Management since 2009. To date, over 188 industrial facilities have participated in SEM. A key tool used in SEM is Monitoring, Targeting, and Reporting (MT&R) models. Customers and program implementers use MT&R models to estimate and track site energy savings. The MT&R models are customized for each customer, and different models are developed for gas and electric consumption. Developing and maintaining MT&R models accounts for a significant portion of the cost of delivering SEM. If the MT&R modeling process could be streamlined, with reduced-form models (i.e. fewer variables) and a more consistent set of variables that still provide comparable results, the cost of delivering SEM could go down. For this analysis, we investigate the following two questions:

- What are the characteristics of models developed for SEM?

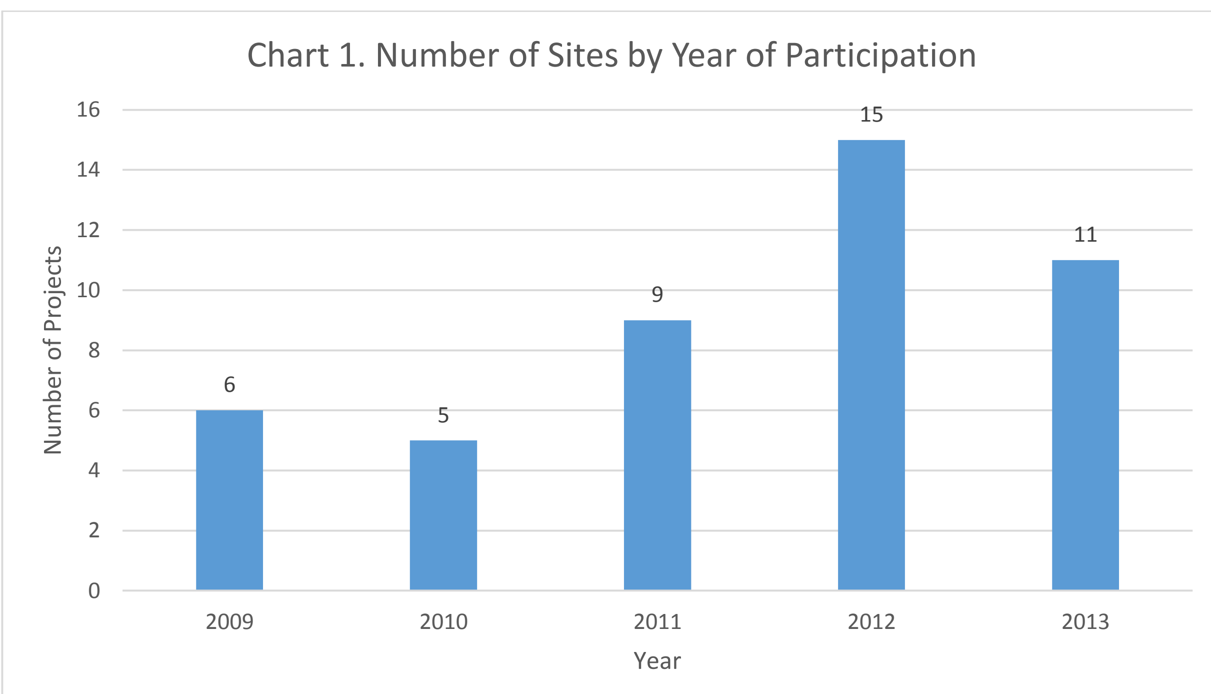
- Are there ways to simplify and streamline model development?
- How well do the simple models perform compared to the models used to estimate savings?

In the next section, we provide a summary of model characteristics for a set of participants that participated between 2009 and 2013. We provide a set of rules used to simplify model. Simplified models are developed for all the available MT&Rs. The simplified and original models have their savings re-estimated using the same set of data and a pre-post specification. The predictive results as well as the explanatory power of the different models are then analyzed.

Model Characteristics

The analysis looks at the 59 SEM customer facilities that were in the sample selected for the Energy Trust's Production Efficiency Program 2012-2013 impact evaluation and a separate Industrial SEM Process and Impact evaluation. Energy Trust was already collecting and aggregating the data for these SEM participants to deliver to the evaluation contractor, and the samples had been part of the independent evaluation sample designed to be representative of the program.

As with most projects, there was attrition with this sample. For five of the sites the MT&R workbooks could not be located. An additional eight sites dropped out of the final sample because the data contained in the workbooks was incomplete (e.g. no pre or post period or no data on variables that were used in the final model). Forty-six sites were used in the final analysis and their participation represents a good cross section of the years the service has been offered. These 46 sites had a total of 71 electric models and 27 gas models.



Most of the sites have from one to three models. Only some of this is due to natural gas and electricity having separate models. The presence of multiple models has more to do with the fact that industrial sites are often large and complex and many have discrete industrial processes that are sub-metered.

The frequency of the data varied by fuel type. Gas models depended primarily on monthly data with over 80% of the models using their utility bills to populate the models, with weekly data representing most of the remainder. For the electric models daily energy and production data were used to construct about a third (32%) of the models, and weekly data made up nearly a quarter (24%) of the models. The remaining models (44%) depended on monthly data. An analysis of how data frequency might impact the variance of model savings estimates, though of interest, was not pursued as part of this paper, but should be considered for future research.

Model Specification

The MT&R models are typically specified as:

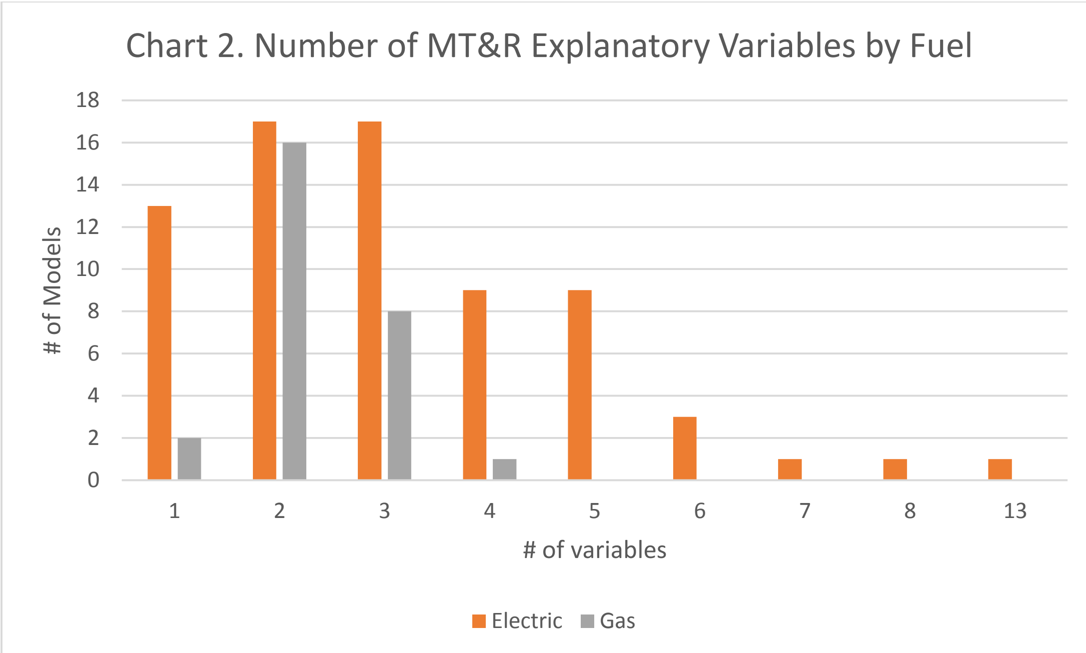
Energy = f(Production, weather, other)

Where energy can be a function of one or more production variables, one or more weather variables and other variables.

The MT&R models included in this study used up to six different production variables. Electric models tended to have the most with over half (55%) having two or more production indicators as explanatory variables. For gas, most of the MT&R models (60%) were not correlated with a production variable, and most of the remaining models (30%) used only one production variable. Most of the industrial customer that have gas models are not large users of gas. The reason for this is that in in Energy Trust's service territory large users of gas are usually transport customers. Transport customers purchase their gas directly in the open market and pay the gas utility a transport charge. As transport customers do not pay into the public purpose charge in Oregon, they are not eligible to receive SEM services in regards to their gas consumption, therefore no gas model is developed. In many cases, the additional production variables used in both the gas and electric models are transformations of one of the other specified production variables (e.g. production squared). Transformations are used to model a possible nonlinear relationship between production and energy consumption.

The MT&R models used a wide variety of weather variables, such as outside air temperature, wet bulb temperature, heating degree-days (HDD) and cooling degree-days (CDD). In addition, many models include a variety of transformations for these variables (e.g. the inverse of the square root of the outside air temperature) that model nonlinear relationships. Half (49%) of the electric MT&R models did not use any weather variables in their models, while a third used only one. MT&R gas models overwhelmingly (71%) used two weather variables.

In all, over half (58%) of the electric and three quarters of the gas MT&R models use three or fewer explanatory variables (Chart 1). That still means that 42% of the electric models have four or more variables, and in one case thirteen. There is still the issue of consistency, as the model developers use a wide set of weather variable that are modeling a nonlinear relationship between weather and gas consumption.



The resources spent on MT&R model development and specification to obtain a highly accurate model are understandable, from a program implementer's standpoint. The implementer wants to provide a customer with a model that explains as much of their energy consumption as possible, and identify those variables that are driving it. An accurate model in turn provides the customer guidance on what types of energy efficient actions to take, the ability to track and report the savings and greater confidence in the savings and their investment decisions. The SEM program managers also have an interest in highly accurate models, as they will provide more accurate savings estimates, and allow the program to better forecast and meet its goals. This is especially important for programs, such as SEM, that rely on largely behavioral effects to generate savings, and have had their savings assumptions questioned.

After a review of these models there were two areas of concern, that of over-specification and spurious regression. Over specification is when additional variables are included in the model that do not add significantly to its explanatory power. This issue will not impact the accuracy of the model but may make interpretation of the model more difficult, and add to the costs of developing and maintaining the model. An example of the interpretation issue, is when two production variables are included that are highly correlated. In this case, the variance of the estimated coefficients will increase and the interpretation of the coefficients will not be straightforward, as the two production variables will be not be independent of each other. Additional cost and resources are needed to collect the additional variables data, as well as run and analyze these additional models. Spurious regressions results are those where variables are only randomly correlated with the dependent variable, thus falsely indicating a causal relationship. Spurious regression results occur often with times series data (Granger 1990). Therefore, it is important for the model specifier to have a strong theoretical reason for including variables in the model.

Simplified Model

The simplified model form that is used to compare to the MT&R models follows the same general form and is based on the same data set. Where the simplified model differs from the MT&R model is that:

- The number of production and other variables used in the model is minimized
- A consistent set of weather variables is used across all models
- Nonlinear transformations of variables are not used
- Estimated coefficients of all variables should have a theoretically consistent sign (e.g. production needs to be positively correlated with energy)

To compare the MT&R and the simplified model specifications the same set of data are used. To obtain a savings estimate for each model a pre/post model specification is used[1]. In essence, a dummy variable indicating the post-participation period is included in the model. A nice property of using a dummy variable is that the coefficient can be easily interpreted as the change in daily consumption associated with SEM implementation.

Another reason for taking a more simplified route is that the model is meant to be used by customers to track their performance. Many SEM customers are not familiar with regression analysis and model development. Therefore, starting with a simple model, with few explanatory variables and easy to interpret coefficients can make the MT&R introduction to customers easier. Specifying only one production variable will allow for a straightforward interpretation of the coefficient. In this case, a one-unit increase in production will lead to the value of the estimated coefficient increase in energy consumption. Since production and energy have an expected positively correlated relationship, the coefficient is expected to have a positive sign. The same is true when considering CDD and HDD as weather variables. HDD and CDD are typically used to represent the effects of weather in a billing analysis model. If heating loads are expected, a positive relationship between HDD and energy can be expected, and if the coefficient is negative, this would indicate that no heating load is present. The coefficient also has a clear interpretation, which is every degree the outside temperature is below the specified HDD reference temperature, unit energy will increase at by the value of the coefficient.

This is not to say that a more detailed and complicated model will not achieve higher accuracy. . However, this additional detail comes at a cost. One additional cost is the of additional data collection, as additional data will have to be collected and maintained. A second cost is program implementation costs. MT&R model development can take up additional time and resources as model specification, training and maintenance all require resources. Program management costs can also increase, as model review and data management costs will increase with the diversity of models and number of variables that are used. Evaluation costs may also increase, as updating model estimates, that include a wide set of variables, require additional resources, and analysis may be more resource intensive with detailed analysis of individual models rather that models in aggregate.

The simplified model specification rules of thumb were:

- Use only uncorrelated production variables. Additional production variables could only be included if they were minimally correlated. Minimal correlation was defined as having a

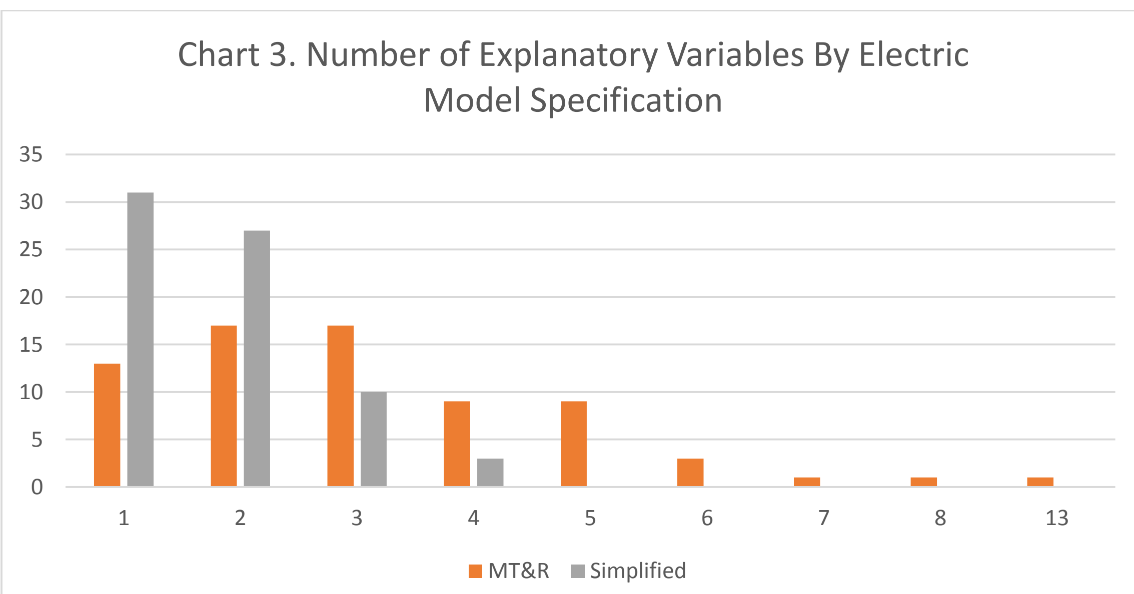
[1] One study has found that the pre/post model specification yields similar savings estimates as models with additional post period interactive terms. (SBW 2016).

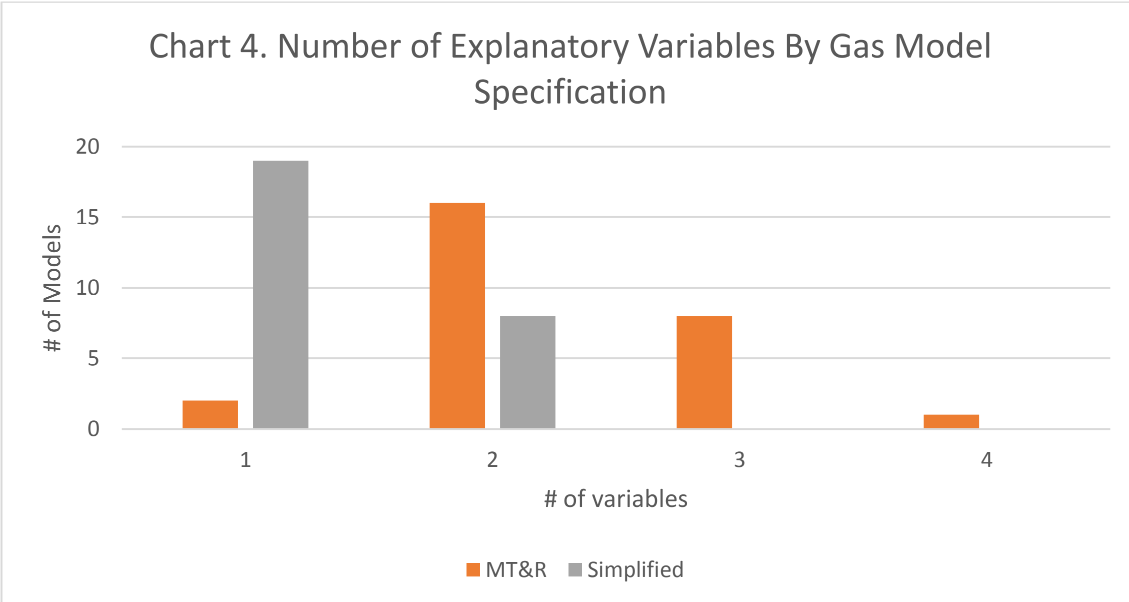
correlation coefficient of less than 0.5. The use of uncorrelated production variables should provide estimated coefficients that have unambiguous interpretations.

- The production variable had to be positively correlated with energy use (i.e. the estimated coefficient had to have a positive sign).
- Use only HDD and CDD with a fixed reference temperature (in this case 60 degrees Fahrenheit were used). The reason for this is that HDDs that are calculated using different reference temperatures (i.e. HDD ($T_{60°}$) and HDD ($T_{65°}$)) are highly correlated with each other and are good proxies for each other. As the SEM program is not interested in researching the changes in reference temperature, it is an unnecessary complication to do a grid search for the reference temperature that provides the best fit.
- In most cases, we would expect the relationship between the HDD/CDD and energy consumption to be positive and would not include the respective weather variable in the model specification otherwise.
- In most cases, dummy variables and other variables were not included in the simplified model. Many of the variables used in the MT&R model specifications mirrored production (e.g. a plant shutdown, holidays, weekends, strike, etc. where the production was also zero). In some models, the dummy variables were retained, as they indicated other non-SEM energy efficiency program measures or when they were the only plant operations variable available.

Using the above guidelines, all of the 98 MT&R electric and gas models went through a re-specification process. In fourteen cases, the simplified model and the MT&R model had the exact same specification, as only one explanatory variable was used in the model; production. This only occurred with electric models. Gas models all included one form of weather variable or other but not the HDD with a fixed reference temperature that was consistently used in the simplified model.

The median reduction in number of explanatory variables was two for the electric models and one for the gas. As shown in Chart 3 and 4 below, there was a significant leftward shift indicating a reduction in the number of variables.





The number of variables is only one indicator of the complexity of models. Another form of reducing complexity is standardizing on the variables. Using only HDD and CDD with one fixed reference temperature certainly simplifies data gathering and specification. Not allowing a variety of transformed variables to be included in the models can reduce the initial time and resources needed for model development.

Of course, simplification for simplifications sake is not the goal of this analysis. What one wants to know is how comparable the outcomes of the MT&R and simplified models are. The two models will provide different results, but how different are the results, and is the difference meaningful, are questions that are of interest.

Gas Model Comparison

A comparison of the average R-squared of the twenty-seven simplified and MT&R gas models indicated that both model specifications have a similar overall explanatory power, with the simplified model having, on average, an R Squared of 0.83 and the MT&R models having, on average, an R Squared of 0.86. A T-test of the means of the R squares for the simplified and MT&R models indicated that they were not statistically different from each other at a 95% confidence level.

When looking at the average estimated savings, the MT&R model savings were estimated to be an average of 9.8 therms/day, versus the simple model average of 25.5 therms/day. Much of this difference was due to one outlier site that represented nearly half the absolute difference in savings between. After removing this outlier, the difference in estimated average savings was reduced with the MT&R and simplified models respective average savings being estimated at 8.1 and 14.9 therms/day. T-tests run on these savings estimates indicate that there was no statistically significant difference between the means of the savings estimate by the simplified and the MT&R models at a 95% confidence level. The gas savings estimates from each model on average had high variances, and both were not statistically different from zero. This results in annualized savings of 2,952 therms /year for the MT&R model and 5,439 therms /year savings for the simplified model. This represents a modest overall reduction for all the sites pre-participation gas consumption of 3.1% for the simplified model and 1.7% for the MT&R model.

Electric Model Comparison

A comparison of the electric MT&R model and the simplified models also shows that the two models in aggregate provide similar levels of accuracy in explaining energy use, with an average R-squared being 0.80 and 0.75 respectively. Again, the difference in means of the R-squares is not statistically significant at the 95% level. When looking at the projected savings, the average savings from the MT&R model were 1,436 kWh/day and 728 kWh/day for the simplified model. This result was highly influenced by two outliers that represented nearly two thirds of the absolute difference in savings estimates of the simple and MT&R models. One site's MT&R and simplified models both generated statistically significant savings coefficients that had opposite signs. The other site estimated savings coefficients that had very large differences. In this case, the MT&R model projected very high increases in energy consumption and the simplified model indicating minimal, to no change, in consumption due to SEM participation. After removing these two outliers, the savings averages of the remaining 69 sites MT&R and simplified models were found to be in the same range, with the MT&R model estimating a 1,645 kWh/day reduction in electricity and the simplified approach showing a 1,323 kWh/day reduction. Both of these savings estimates was statistically different from zero at the 95% level. A T-test indicated that there was no statistically significant difference between these two averages at the 95% confidence level. This represents a modest overall average reduction with the simplified models showing an average 3.1% reduction in consumption and the MT&R models estimating a 3.9% decrease in energy consumption.

Conclusion

A SEM model specification that employed a reduced set of variables was estimated and compared to MT&R SEM models that had been developed for Energy Trust's SEM program in the years 2009-2013. The simplified specification resulted in a reduction of variables used in both electric and gas SEM models. The median reduction in variables was two for electric models and one for gas models. The simplified specification resulted in electric models with a maximum of four explanatory variables, while the MT&R specification had a maximum of thirteen. For the twenty-seven gas models compared, the simplified model specification contained a maximum of two variables, while the MT&R specification maximum was four explanatory variables. Simplified models reduced the number of variables in each model by restricting specified variables to those that had low correlation to each other and were not transformations of already specified variables. The set of variables used between models was also reduced in the simplified model, as the only weather variables considered for inclusion were restricted to HDDs and CDDs with one fixed reference temperature.

The comparison of the two different specification methods resulted in the estimation of gas and electric models for most sites that are not dramatically different in both explanatory power and savings estimation. These results support the consideration of using the simple model specification process outlined in this study to provide a framework to develop an initial SEM baseline model. The simple model should be easy to develop at the beginning of a customer's SEM engagement. All that is required from the customer is their production data. In most cases, the utility consumption data should be available to the SEM implementer. If the customer has sub-metered processes, this sub-metered data can be used as the source of energy data. The SEM implementer is also probably best placed to identifying the most appropriate weather station to pair with the customer's site, and provide the HDD and CDD data at the same frequency as the production and energy data. Based on the results of this study, the simplified set of variables should be able to generate an initial model that will come close to the accuracy of a final more detailed model, as many of the strong drivers of energy use will have been included. This study does not argue for the simple SEM model specification to be the final model that the customer uses. However, the simplified model does provide a good baseline model from which to test what other variables should be added to achieve a model with higher accuracy.

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