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THESIS

**STUDY OF NAVAL WHOLESALE INVENTORY
OPTIMIZATION MODEL**

by

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September 2020

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STUDY OF NAVAL WHOLESALE INVENTORY OPTIMIZATION MODEL

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ABSTRACT

Navy Supply Systems Command manages a vast inventory of items to meet the fleet's requirements. A requisition decision for restocking an item is made, in part, based on the planned minimum safety stock (PMSS) level. The Wholesale Inventory Optimization Model with Enterprise Resource Planning (WIOM-ERP) simulates the fleet's requirement demand based on historic data to establish metrics that serve as the basis to recommend the PMSS levels. NAVSUP uses WIOM-ERP to balance its inventory between procurement persistence (avoidance of "churn") and fulfillment of demand (fill rate). WIOM-ERP provides the flexibility for planners to weigh the importance of each metric and shift the balance between churn and fill rate. Decision makers seek insight into the relative tradeoff between churn and fill rate, resulting from changing the weight of each metric. This study applies a high-dimensional statistical design of experiments to simulate different combinations of metric weights for the WIOM-ERP user inputs. The output of WIOM-ERP is recorded for each design point to calculate measures of performance (MOPs) for churn and fill rate. The data are analyzed by developing statistical metamodels for each MOP to determine the impact on the metrics of the factors, their interactions, and the resulting tradeoffs between different combinations of weights.

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LIST OF ACRONYMS AND ABBREVIATIONS

CSV	comma-separated value
DES	discrete event simulation
DOD	Department of Defense
DOE	design of experiment
MOP	measure of performance
NAVSUP WSS	Naval Supply Systems Command, Weapon Systems Support
NOLH	nearly orthogonal Latin hypercube
NPS	Naval Postgraduate School
PID	percent of items with deviation
PMSS	planned minimum safety stock
QL	quadratic loss
QLF	quadratic loss function
RBS	readiness-based sparing
RCT	Run Control Tool
WIOM-ERP	Wholesale Inventory Optimization Model for Enterprise Resource Planning

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EXECUTIVE SUMMARY

Naval Supply Systems Command, Weapon Systems Support (NAVSUP WSS) manages Navy's inventory to meet the Fleet's operational and maintenance requirements. Inventory exists because supply and demand are difficult to synchronize perfectly and it takes time to perform material-related operations. NAVSUP WSS's aim is to maximize the fraction of filled demands (fill rate), but the constant adjustment (churn) to the changing demand creates an administrative burden that requires extensive labor, mainly due to contract modification for requisition of items. In other words, while in support of maximizing fill rate it might make sense to adjust the safety stock parameters whenever new demand information is obtained, this will create churn, and additional expense, in the form of the required contract changes and associated administrative burdens. On the other hand, maintaining an expected high level of the planned minimum safety stock (PMSS) levels can increase fill rate, but it increases the carrying cost of the inventory.

Wholesale Inventory Optimization Model for Enterprise Resource Planning (WIOM-ERP), a computer program that combines the versatility of simulation with the utility of optimization, provides a balance among the fill rate, churn, and carrying cost. A discrete event simulation uses historic data to generate scenarios of expected fill rate and inventory carrying cost for different PMSS levels of each item. Churn for each PMSS level is calculated deterministically. The optimizer's objective is to find a set of PMSS levels that maximizes the expected fill rate and minimizes the churn for all items simultaneously without the expected carrying cost exceeding the budget. WIOM-ERP also provides the flexibility for planners to "weigh" the importance of each metric in achievement of a balanced inventory among fill rate, churn, and cost.

NAVSUP WSS is interested in studying the output response of WIOM-ERP to understand how variations of 14 input variables would affect the expected fill rate and churn both globally and by item groups designated as *bands A* through *D*. For this research, NAVSUP WSS supplied us with the items in the maritime, non-nuclear, consumable inventory database. We design an experiment with input ranges chosen to produce outputs

that would provide valuable insights into WIOM-ERP outcomes. We use two types of measures of performance (MOPs) to record the outputs of WIOM-ERP:

- PID, which assess the *percentage of items with deviation*, regardless of the deviation magnitude, from the target value for fill rate or churn within the population.
- QL, which assess *quadratic loss* from the target value for fill rate or churn across the items.

For example, when comparing the churn MOPs, *band C* may have higher PID value than *band D*, but the QL value in *band D* may be higher than *band C*. This indicates that *C* has a higher average proportion of items with churn, while the lower quadratic loss carries the interpretation that the *C* outcomes are less prone to large deviations from the target value of zero. Conversely, *D* has a larger QL because of bigger extremes when churn is non-zero.

Our design of experiments (DOE) consists of 65 design points that are stacked 14 times providing 1,025 unique variations, and there are 20 MOPs. Running the 1,025 design points via the graphical user interface of WIOM-ERP and recording the MOPs manually is a time-consuming activity, and prone to human errors. We bypass the user interface and create the Run Control Tool (RCT) to automate the process. RCT is developed in the R-programing language. It generates the user inputs of 14 parameters and interacts directly with the optimization component of WIOM-ERP for the computation and recording of the MOPs.

We create descriptive metamodels—statistical models of the simulation model—using stepwise regression to sort through all the two-way interactions and variety of non-linear alternatives in addition to our main factors. The stepwise regression tool eliminates those terms that have low information content for predicting the response surface of the MOPs using Bayes Information Criterion. We use the descriptive metamodels to study the trends of QL and PID MOPs with respect to the input variables.

The QL and PID MOPs for fill rate are sensitive to the budget constraint. As the budget constraint decreases the QL and PID MOPs for fill rate increase, indicating that WIOM-ERP PMSS level recommendations are more likely to deviate from their target fill rate. Decreasing the churn weight to near zero leads to a slight improvement in global fill rate, but it causes significant churn. This observation validates prior research that large reductions in churn incur extremely minimal decrement to target fill rates. We also observe that the response surface of QL MOP for global churn follows the same trend as churn in *band A* in response to changes of churn weight and budget constraint. We conclude that global churn is driven by churn in *band A*. It is also noteworthy to mention that budget for inventory carrying cost does not affect the outputs beyond a certain level. This observation can prevent setting an unnecessarily high inventory budget in advance.

DOE is a versatile technique for studying complex computer programs such as WIOM-ERP and its performance on NAVSUP's inventory planning. We recommend using DOE to understand the tradeoffs between metrics in other than the maritime, non-nuclear, consumable NAVSUP inventory or for measuring the performance of future iterations of inventory optimization systems.

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I. INTRODUCTION

Effective logistical support is vital to sustained global military operations because this support directly affects operational readiness, lethality of weapon systems, and quality of life for military personnel. Strategic logistics focuses on creating infrastructure with balanced expenditures in the areas of technology, industry, inventory, storage, and transportation. There are several levels of inventory management; inventory that is centrally managed is called wholesale inventory. Our research examines a software model that optimizes wholesale inventory levels for the U.S. Navy.

A. BACKGROUND

Naval Supply System Command, Weapon Systems Support (NAVSUP WSS) manages a large inventory of consumable and repairable items to meet customer requirements for operations and maintenance. Critical concerns that decision makers must answer to properly manage inventory levels for each item include when and how much to buy. For each item managed by NAVSUP WSS, the decision to perform a replenishment action (i.e., a purchase or repair requisition) depends, in part, on the item's planned minimum safety stock (PMSS) level.

In accordance with the Department of Defense (DOD) supply chain business practices (DOD 2018), NAVSUP is implementing the latest version of the simulation-optimization tool called Wholesale Inventory Optimization Model for Enterprise Resource Planning (WIOM-ERP). WIOM-ERP is the first version of NAVSUP WSS's inventory management programs that integrates "simulation-optimization" architecture to enhance the effectiveness of wholesale inventory policy, which forms "the backbone of the Navy supply system" (*Navy Supply Corps Newsletter* 2019). This wholesale inventory policy effectiveness is achieved by balancing *fill rate* (percentage of fulfilled demands), *churn* (persistence in units of replenishment), and inventory cost.

We use fill rate as a metric for the measure of performance (MOP) because timely and cost-effective delivery of material is the measure for total supply chain performance (DOD 2003). Churn is also an MOP because changing the replenishment quantity for each

item increases the administrative burden of inventory, mainly due to management of contract modification for that item's requisition. Consequently, the WIOM-ERP objective is to find a set of PMSS that minimize a weighted sum of (i) a (typically convex) function of expected fill rate shortage, and (ii) absolute churn deviation, for all items simultaneously. Each item's PMSS incurs an expected inventory carrying cost, thus the tradeoff between the achievement of fill rate and churn, and total cost.

The optimization model in WIOM-ERP works in conjunction with a discrete event simulation (DES) model that generates scenarios with estimates for various metrics, including the abovementioned ones, for each item. The DES simulates each item's demand and estimates expected fill rate and inventory cost for each PMSS level. Other metrics such as churn can be measured without a simulation. For example, increasing the PMSS level from 3 to 5 units will increase the churn by 2 (Salmeron and Craparo 2019, p. 3). The various metrics generated by DES are used as inputs for the multi-objective function and budget constraint of WIOM-ERP.

WIOM-ERP provides the flexibility for planners to "weigh" the importance of each metric in achievement of a balanced inventory between cost and fulfillment of the fleet's expected demand. For example, if persistence in replenishment quantity is more important than fulfilling the predicted customer demand, the relative weight for minimizing deviation (from the absolute churn target of zero) must be set larger than that of minimizing the expected deviation below a target fill rate. By studying the different outcomes of WIOM-ERP for varying ratios of the metric weights planners can gain insight into metric achievement tradeoffs and strengthen confidence in their ability to set PMSS levels that satisfy the inventory policy per DOD instructions.

B. LITERATURE REVIEW

In this section, we review previous studies on the legacy versions of the WIOM-ERP as well as other simulation-based optimization models used by NAVSUP. This creates a framework of continuity for this thesis. We will also closely review the mechanics of WIOM-ERP optimization and discuss the use of design of experiments (DOE) in

sensitivity and influential factor analysis. But first, we provide a quick overview of NAVSUP WSS's inventory management.

1. NAVSUP WSS Inventory and Material Management

Inventory and material management is a problem common to many organizations in a variety of sectors of the economy. If we ask inventory managers about the purpose of inventory, they may say that “inventory exists because supply and demand are difficult to synchronize perfectly and it takes time to perform material-related operations” (Tersine 1996, p. 6). NAVSUP WSS procures new items direct from the manufacturers, as well as managing the repair of items through either the manufacturers or Navy's repair depots. These items are then “sold” to the fleet. The fleet pays for the parts with dollars appropriated by congress. NAVSUP WSS's wholesale inventory problem is concerned with the requisition (purchase or repair) of manufactured goods for distribution to naval vessels and air wings in order to satisfy their requirements.

The basic economic parameter of an inventory model is the inventory cost, which is divided into ordering cost and carrying cost of the items in the inventory. The ordering cost is the sum of the administrative expenses associated with the requisition itself, regardless of its quantity. The carrying cost of an item is the purchase or repair price of that item as it is placed in the inventory, and it depends on the quantity. The metric of churn is of interest to NAVSUP WSS because any change in the ordering quantity of an item may require a contract modification that leads to an increase of ordering cost in the inventory. Satisfying every demand with a fill rate goal near 100% requires carrying excessive inventory for each item, which drives the inventory cost very high.

Two of methodologies that the Navy uses for inventory and material management are readiness-based sparing (RBS) and demand-based model. RBS is an inventory methodology to meet weapon system availability requirements at minimum cost. RBS is used to set retail inventories, that is the inventory held at each Naval unit for use by maintenance organizations. Wholesale policy is governed by a demand-based model, which is an inventory methodology based on the forecast of annual demands for

determining stockage at minimum cost (DOD 2003). WIOM-ERP is designed to find the optimum stockage level for the demand-based inventory at the wholesale level.

Forecasting future demand from the historic data is done using time series analysis. The DES model of WIOM-ERP replicates NAVSUP WSS decision process, which is based on the abovementioned demand forecast. This process, called Distributed Requirement Planning anticipates when the demand forecasts will breach the PMSS, triggering a recommendation to purchase or repair. In addition, the DES simulates the historical demand, producing a more realistic estimation of the metrics with the assumption that the future will be similar to the past. As a result, it generates expected fill rate and other metrics for the given PMSS levels. These metrics are used as input to the optimization model.

2. Sensitivity Analysis

Running an experiment is costly and time-consuming regardless of whether we are studying an actual process or a virtual one. The method of designing a set of inputs for the process to produce the outputs that would provide the most insight into the workings of the process is called design of experiments (DOE). In other words, a well-developed DOE enables us to gather as much information as possible from a limited number of observations (Sanchez et al. 2017). Investigating the amount and direction of variation in the outputs as a result of a small change in the inputs is called sensitivity analysis.

In this thesis, we use a high-dimensional DOE to analyze the sensitivity of WIOM-ERP achieved fill rate and churn to small variations in the input metrics. We will also study the influence and interaction of inputs on the WIOM-ERP outputs. Similar analysis is done by Pfaff (2017) in his study of the Navy Aviation RBS model using DOE. He uses the data from multiple trials to perform a stepwise regression and identifies the most impactful factors along with the best metamodel—a statistical model of the simulation model—for estimating the NAVARM cost of inventory for a given target level of readiness.

3. Previous WIOM Studies

Roth (2016) develops a comparative inventory simulation with three methods for selecting PMSS levels. He first uses a simple model that forecasts the future demand based

on mean and standard deviation of the historic demand. His second model is the third-party software developed by a NAVSUP contractor called Service Planning and Optimization; the algorithm used in that proprietary software is unknown. His third method is the first generation of WIOM that was newly developed at Naval Postgraduate School (NPS) now replaced by WIOM-ERP.

Roth compares the effectiveness of these three methods of calculating PMSS by developing a DES tool and comparing the simulated fill rate from each method. He concludes that WIOM performs better than both the simple model and the third-party software used by NAVSUP at the time.

Teter (2018) continues Roth's work by conducting a series of experiments on the legacy version of WIOM to gain insight into relative tradeoff between churn and fill rate as well as studying the effects of WIOM periodicity on fill rate. Periodicity refers to the length of time that the PMSS solution of WIOM remains implemented. In other words, periodicity is the amount of time that it takes for NAVSUP WSS to re-run WIOM (e.g., quarterly), understanding that more frequent runs allow for PMSS adjustments to changing demands but also incurs other administrative and manpower costs. Periodicity can therefore be viewed as its own parameter, one that potentially affects both churn and fill rate.

Teter studies the impact of running WIOM at different periodicities and with different persistence parameters. He discovers that WIOM performs best with a quarterly periodicity. He also discovers that churn can be reduced by 99% without affecting the predicted fill rate. The limitation in Teter's research is that his model is restricted to deterministic historical demand and unable to test the robustness of the system to changes in demand. He concludes that further research is required to confirm the generality of his findings.

4. WIOM-ERP Multi-Objective Function

WIOM was developed by NPS as an inventory management tool for NAVSUP WSS and has been through several revisions since October 2013. In this thesis, we study one of the latest versions of the software, known as WIOM-ERP version 5.5. "As a tool,

WIOM-ERP comprises a series of mathematical optimization models, algorithms, and their computational implementations, which can be used by NAVSUP planners to help guide wholesale inventory decisions” (Salmeron and Craparo 2019, p. 1).

The optimization model of WIOM-ERP is based on a multi-objective function that allows flexibility to seek globally optimum PMSS levels while observing several constraints over multiple metrics for each item. For example, WIOM-ERP can choose PMSS levels for all items j in order to minimize expected fill rate deviation down (E_FR_DD); minimize absolute churn deviation up ($AbsChurn_DU$); and enforce the constraint for safety stock cost (E_SS_Cost) not to exceed a certain budget (agg_v_max). The mathematical representation is shown by Equation (1).

$$\begin{aligned}
 \min \quad & w_{EFR} \sum_j (p_{EFR,j} \cdot E_FR_DD_j)^2 + w_{AbsChurn} \sum_j p_{AbsChurn,j} \cdot AbsChurn_DU_j \\
 \text{s.t.} \quad & 0 \leq \sum_j E_SS_Cost_j \leq agg_v_max
 \end{aligned} \tag{1}$$

In Equation (1), for each item j the terms E_FR_DD and $AbsChurn_DU$ are functions of the chosen PMSS for the item (not shown in this formulation, for conciseness). DU and DD stand for Deviation Up and Deviation Down from target values, respectively. The item-dependent terms p_{EFR} and $p_{AbsChurn}$ are the pre-calculated penalty terms based on item demand. This flexibility of WIOM-ERP allows planners to include or exclude metrics and constraints to the optimization model. Planners can set the metric weights, denoted by w_{EFR} and $w_{AbsChurn}$, in order to change the importance of those metrics and achieve PMSS levels that suite NAVSUP’s changing budget and policy goals.

C. SCOPE

In this thesis, we develop a DOE for the weights, penalties, and budget input values of WIOM-ERP 5.5, and analyze the sensitivity of the solution to changes in those input values. The study is limited to the non-nuclear consumable inventory provided by NAVSUP WSS in March of 2020.

We also develop an R-script tool that runs the DOE and calculates the MOPs for studying the tradeoffs between the overall fill rate and overall churn. NAVSUP WSS planners will be able to use this analysis to gain insight into those tradeoffs and anticipate how model inputs affect their metrics of interest.

D. THESIS FLOW

The remaining chapters of this thesis are as follows: Chapter II describes the methodology used for conducting the sensitivity analysis, Chapter III analyzes the data that is used to study the tradeoffs between overall fill rate and churn and the results of the sensitivity analysis for running the WIOM-ERP on the non-nuclear consumable database to describe the tradeoffs associated with using different weights. Chapter IV provides the conclusions and recommendations based on the sensitivity and influential factor analysis of the metric weights in WIOM-ERP output.

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II. METHODOLOGY

In Chapter I, we reviewed the background of the NAVSUP WSS WIOM-ERP model and the use of DOE in system analysis. In this chapter, we discuss the database and the Run Control Tool (RCT) that we have developed to use for generating data and conducting the analysis of WIOM-ERP. Our RCT simulates different user inputs into WIOM-ERP based on each design point of our DOE, and runs the optimization model. The output of WIOM-ERP for each simulated design point is recorded for the calculation of the MOPs.

A. RUN CONTROL TOOL

The common user of WIOM-ERP interacts with the software via a graphical user interface. However, our RCT uses the optimization model in WIOM-ERP as stand-alone software. This requires the ability to write comma-separated value (CSV) files, which contain data such as individual item metrics and budget, among others. CSV files produced by WIOM-ERP include recommended PMSS levels and predicted fill rate and churn for each item. These metrics are read in by the RCT, and they are merged with all the relevant data into one output file for our analysis.

We have developed the RCT in R programming language. RCT runs the Microsoft Windows executable *WIOM_ERP.exe* version 5.5 (Salmeron and Craparo 2019) optimization software. Figure 1 illustrates the input and output architecture of our RCT. The shapes that are shaded in *blue* identify the components that have been developed for this thesis, and those in *black* were developed by NAVSUP WSS.

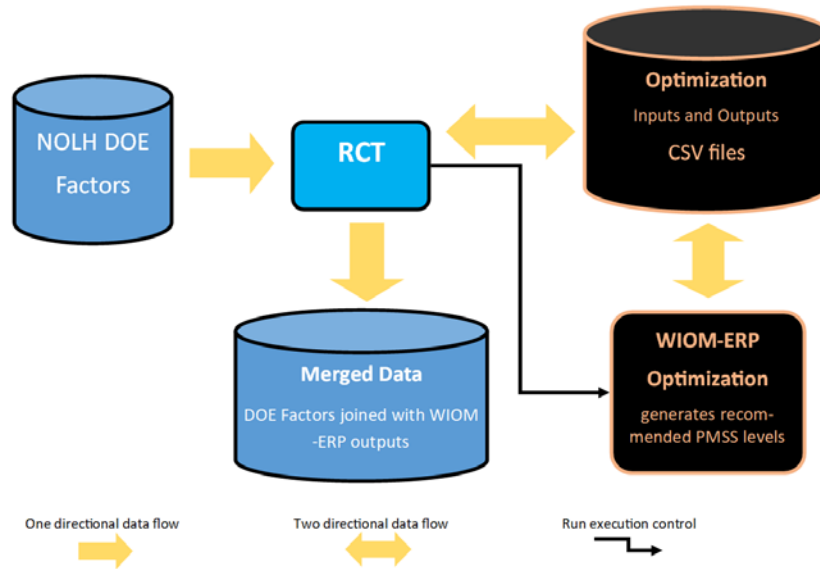


Figure 1. Simulation tool architecture

We have used a nearly orthogonal Latin hypercube (NOLH) generator script called *stack_nolhs.rb* (Sanchez 2018), written in the Ruby programming language (Matsumoto 1995), to construct 14 stacks of a 65 level design, yielding 1,025 design points. The stacked DOE allows us to examine each level of a factor in a variety of combinations for factor pairings. After constructing the NOLH DOE for our 14 factors at 1,025 levels, we use the RCT to generate data for our analysis. Figure 1 outlines the three steps of the RCT:

- In the first step, RCT reads each design point from the DOE and writes it to the corresponding CSV file of the optimizer for that factor.
- In the second step, the RCT runs the stand-alone optimizer of WIOM-ERP for each set of design point values. Upon completion of the optimization task, the PMSS levels, fill rate, and churn values for each item are updated in the optimization CSV files.
- In the third step, RCT reads the fill rate and churn from the optimization CSV files for each item, calculates the MOPs for fill rate and churn, and merges the MOPs for each design point with the factor values of that

design point into an output file. We use the merged output file for the analysis.

B. DATA REVIEW

NAVSUP WSS has provided a database for our analysis containing the maritime, non-nuclear, consumable items. There are 3,530 items in the database and the items are divided into four categories, also known as *bands*.

There are four *bands* designated as *A*, *B*, *C*, and *D*. *Banding* is a way of designating item priority, with regard to both contracting and funding, based on the number of demands for an item. For example, the items in *band A* are a small proportion of the inventory, but they represent the majority of the demand. Therefore, it is important to increase the fill rate of these items. While there are general guidelines for assigning an item to a *band* based on its bi-annual demand and priority, with approval, item managers are able to modify item *band* designations.

The maritime, non-nuclear, consumable database contains 266 items in *band A*, 842 items in *B*, 379 items in *C*, and 2,018 items in *D*. There are 25 items in the database that are not designated with any of the abovementioned *band* identifiers. Those items represent less than one percent of the total, and following NAVSUP WSS's guidance, they have been excluded from the analysis.

In the maritime, non-nuclear, consumable database, target fill rates are as follows: 95% in *band A*, 90% in *band B*, and 85% in *bands C* or *D*. All *bands* have a target churn of zero. The individual item penalties for not meeting their target fill rate and churn vary based on the item demand, and have been pre-calculated for each item in the database. The pre-calculated penalty values are used as the baseline to build the factors for our DOE.

1. Factor Selection

One of the important steps in developing a DOE is the selection of the factors to be used as a user's simulated inputs. NAVSUP WSS is interested in 14 factors, as shown in Table 1. We keep the value of the global weight for expected fill rate deviations below the target at a constant 1.0. Since this term appears in the objective function of the optimization,

we can reproduce any other value by modifying the weight of the other objective terms (specifically the churn weight) as long as we maintain the relative ratio between them.

Table 1. Factors

Factor Name	Description	Range	Type	User-Provided Values
w_DevUp	Weight of global churn penalty	$[10^{-5}, 10^{-1}]$	Value	0.05
agg_v_max	Budget constraint (Million \$)	[5.7, 42.4]		38.5
v_min_A	Band A target fill rate	[0.85, 1]		0.95
v_min_B	Band B target fill rate	[0.80, 1]		0.90
v_min_C	Band C target fill rate	[0.75, 0.95]		0.85
v_min_D	Band D target fill rate	[0.75, 0.95]		0.85
p_up_A	Band A item churn penalty	[0.8, 1.2]	Scale Factor	1
p_up_B	Band B item churn penalty	[0.8, 1.2]		1
p_up_C	Band C item churn penalty	[0.8, 1.2]		1
p_up_D	Band D item churn penalty	[0.8, 1.2]		1
p_down_A	Band A item fill rate penalty	[0.8, 1.2]		1
p_down_B	Band B item fill rate penalty	[0.8, 1.2]		1
p_down_C	Band C item fill rate penalty	[0.8, 1.2]		1
p_down_D	Band D item fill rate penalty	[0.8, 1.2]		1

a. Factor Definitions

- The factor w_DevUp is the global weight for churn deviation from the target value of zero. The base value of this factor was set to 0.05 by NAVSUP WSS. Increasing this factor means that we favor more adherence to the legacy PMSS values; in other words, higher w_DevUp values are expected to lead to less churn (on the average) across all items. The practical limit of this factor is from 0.00001 to 0.1. Our preliminary exploration indicates that any value less than the lower limit does not change the fill rate deviations, and any value greater than the upper limit does not change the churn deviations.
- The factor agg_v_max is the budget constraint. Variation in this factor is used to study the effects of budget increase by up to 10 percent or decrease by up to 85 percent from its base value. Any value less than the lower

limit will produce an infeasible solution (because the minimum PMSS levels available require at least that budget), and preliminary investigation reveals that values greater than the upper limit do not change the fill rate or churn deviations.

- The factor v_{min_A} is the fill rate target for each item in *band A*. The baseline value is 0.95, and the variation range is from 0.85 to 1.
- The factor v_{min_B} is the fill rate target for each item in *band B*. The baseline value is 0.95, and the variation range is from 0.80 to 1.
- The factor v_{min_C} is the fill rate target for each item in *band C*. The baseline value is 0.95, and the variation range is from 0.75 to 0.95. The same definition applies to v_{min_D} in *band D*.
- The factor p_{up_A} is the item-specific, churn penalty scale factor, if the item is in *band A*. As such, the individual item value is different, but the same scale factor is applied to each item in *band A*, where this variation is kept the same for all items in *band A*. Similar definition and range rules apply to factors p_{up_B} , p_{up_C} , and p_{up_D} for *bands B, C, and D*, respectively.
- The factor p_{down_A} is the item-specific, fill rate deviation penalty scale factor, if the item is in *band A*. As such, the individual item value is different, but the same scale factor is applied to each of the items in *band A*, where this variation is kept the same for all items in *band A*. Similar definition and range rules apply to factors p_{up_B} , p_{up_C} , and p_{up_D} for *bands B, C, and D*, respectively.

b. Factor Correlations

All factors in our DOE are quantitative and the benefits of using an efficient design are the good space-filling and orthogonality properties it provides. Without orthogonality, effects estimates can be biased. Space-filling provides better resolution on the shape of the

response surface and improved detection of potential lack-of-fit. The NOLH is designed to have virtually no correlation between the factors of our DOE, which allows us to estimate the main effects for all factors without bias due to the presence or absence of other factors. While second-order orthogonal designs exist, they require more design points, so the NOLH was used because of its relative simplicity and cost (Sanchez 2014).

2. Performance Measures

Our goal is to determine the influence of each factor on Measures of Performance (MOPs). NAVSUP WSS is interested in assessing the sensitivity of the WIOM-ERP solution with regards to fill rate and churn for all items both “globally” and within *bands*. As stated in Equation (1), the objective function of WIOM-ERP seeks to balance fill rate and item churn. The function to assess achieved fill rate aggregates items’ penalties for (typically squared) deviations below target fill rate. A similar approach is used for churn, except for the use of absolute deviation. Hence our MOPs use two methods for calculating the performance of each term in the objective function, as described below.

a. Quadratic Loss Function

In robust statistical design, the goal is to minimize *loss*, which is a function of the outcomes designed to penalize deviations from some specified target value τ . Quadratic loss is a popular choice and has the form $L_{Y_x} = c(Y_x - \tau)^2$. Here, L_{Y_x} is the loss, Y_x is the response as a function of input vector x , and c is a “cost conversion” constant which can be used to express the loss in monetary units rather than engineering terms, or to scale the loss suitably for use in multi-criteria decision making. If c is set to one, the result is called “scaled loss.” Under expectation, a quadratic loss function decomposes into two component terms: $E[L_{Y_x}] = c[(E[Y_x] - \tau)^2 + \sigma_Y^2]$. To achieve (expected) low loss, the expected outcome must be *consistently* (as measured by the variance) close to the target value τ .

We use quadratic loss functions (QLF) as MOPs for fill rate and churn, both globally and *band*-specific. Our fill rate loss function is single-sided because we are only concerned with achieved values that are below the target fill rate. In other words, if an item

meets or exceeds its target fill rate, then there is no loss. There is also no reward based on how much it exceeds the target. Our churn loss function is symmetric because any change in churn, above or below the target of zero incurs a cost and is considered a loss. (Note: the churn values associated with each PMSS and item have already been provided as absolute values, so this consideration does not change the outcome of our analysis, but it would if it were provided as positive or negative churn.) Table 2 represents the QLF MOPs that NAVSUP WSS considers for conducting the analysis.

Table 2. Quadratic loss function MOP

MOP Label	Description of quadratic loss functions
$E_FR_DD_QLF$	Global expected fill rate deviation down
$E_FR_DD_QLF_A$	Expected fill rate deviation down within each <i>band</i>
$E_FR_DD_QLF_B$	
$E_FR_DD_QLF_C$	
$E_FR_DD_QLF_D$	
$AbsChurn_DU_QLF$	Global absolute churn deviation up
$AbsChurn_DU_QLF_A$	Absolute churn deviation up within each <i>band</i>
$AbsChurn_DU_QLF_B$	
$AbsChurn_DU_QLF_C$	
$AbsChurn_DU_QLF_D$	

Equations (2) and (3) are the mean square formulae we use for the global QLFs for fill rate and churn, respectively, and are implicitly based on target values of zero.

$$E_FR_DD_QLF = \frac{1}{n} \sum_{j=1}^n (E_FR_DD_j)^2 \quad (2)$$

$$AbsChurn_DU_QLF = \frac{1}{n} \sum_{j=1}^n (AbsChurn_DU_j)^2 \quad (3)$$

Here $E_FR_DD_j$ is the expected fill rate deviation below the target fill rate for item j , or zero if the deviation is above the target fill rate; $AbsChurn_DU_j$ is the deviation from target churn of zero for item j ; and n is the total number of items. For each *band*, we define similar loss function formulae for fill rate and churn as those in Equations (2) and (3), respectively. The only difference is that the sum is calculated only for the subset of

items j within that *band*, and n is replaced by the cardinality of that subset. It is also important to note that the target for QLF measures is zero in all categories of our MOPs.

b. Deviation Ratio

NAVSUP WSS is also interested in studying the percentage of the items that deviate from their fill rate and churn target values. For this purpose, we have used the MOPs described in Table 3.

Table 3. Deviation ratio MOP

MOP Label	Description
$E_FR_DD_percent$	Global percentage of items with expected fill rate below target
$E_FR_DD_percent_A$	Percentage of items with expected fill rate deviation below their target in their respective <i>bands</i>
$E_FR_DD_percent_B$	
$E_FR_DD_percent_C$	
$E_FR_DD_percent_D$	
$Churn_percent$	Global percentage of items with non-zero churn
$Churn_percent_A$	Percentage of items with non-zero churn in their respective <i>bands</i>
$Churn_percent_B$	
$Churn_percent_C$	
$Churn_percent_D$	

Equations (4) and (5) indicate the percentage methods we used for the global ratio MOP of fill rate and churn, respectively.

$$E_FR_DD_percent = \frac{100n_{EFR}}{n} \quad (4)$$

$$Churn_percent = \frac{100n_{Churn}}{n} \quad (5)$$

In Equations (4) and (5), n_{EFR} and n_{Churn} are the number of items with expected fill rate below the target value, and with non-zero churn, respectively. Each *band* uses similar formulae restricted to the items in the *band*. It is important to note that the target for all categories of deviation percentage MOPs is zero.

C. INFLUENCE AND INTERACTION ANALYSIS

We use DOE and regression analysis to study the response surface of WIOM-ERP by mapping the input to output and assess the influence of the 14 factors and their interactions on each of the MOPs. The ability to perform a multi-variable regression with second-degree interactions and non-linearity is afforded by the NOLH DOE.

Analysis is performed using JMP Pro (SAS 2018) statistical software to develop metamodels that allow us to analyze the MOP's response to the influence of the variation in factors. Multiple regression techniques also allow us to assess the influence of interactions between the explanatory variables. *R-square*, residual analysis, and lack-of-fit ANOVA are used to evaluate the fit of each metamodel. The *R-square* value typically indicates what proportion of the total variation of the response is explained by the explanatory variables (Brown 2018). We use various transformations of the response and exploratory variables to match the observed shape of the response surface, and thus to improve our metamodels.

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III. ANALYSIS

In Chapter II, we discussed the tools and methods that we have developed for simulating the user inputs to WIOM-ERP and recording the responses for analysis. In this chapter, we analyze the data that were generated using our RCT to estimate the significant factors and their influence (including non-linear and interaction effects) on the response surface of each MOP. First, we describe the MOPs achieved when the factors are set to *baseline* values provided by NAVSUP WSS. Then, we analyze the MOP response to factor variations. Baseline values and variation ranges are listed in Table 1 in the previous chapter.

A. BASELINE MOP VALUES

The baseline values refer to metric values that NAVSUP WSS planners have used as input of WIOM-ERP to generate PMSS level recommendations for the items in the maritime, non-nuclear, consumable inventory prior to providing the database for our analysis. Table 4 reiterates those baseline values and the calculated MOPs based on the recommended PMSS levels from the output of WIOM-ERP. We have two categories of fill rate and churn MOPs. As shown in Chapter II we group MOPs into two categories:

- QL MOPs: These assess *quadratic loss* from the target value for fill rate or churn across the items in each category, both globally (i.e., for all items) and by *band*. They are based on the quadratic loss functions defined in Equations (2) and (3).
- PID MOPs: These assess the *percentage of items with deviation*, regardless of the deviation magnitude, from the target value for fill rate or churn within the global and *band* population in each category. They are described in Equations (4) and (5).

For example, in Table 4 the percentage of items that deviate from their target churn in *band C* is greater than the percentage of items that deviates from their target in *band D* as indicated by the PID MOP comparison $Churn_percent_C > Churn_percent_D$.

However, for the items that have churn, the magnitude of quadratic deviation for the items in *band D* is greater than that of the items in *band C* as indicated by the QL MOP comparison $AbsChurn_DU_QLF_D > AbsChurn_DU_QLF_C$. In other words, the interpretation of quadratic loss is that while *band C* has a somewhat higher expected churn rate than *band D*, the former is more consistently close to the target of zero because of greater variability in the latter.

Table 4. Baseline value of inputs and calculated MOPs

Factor	Baseline		QL MOP		PID MOP	
<i>w_DevUp</i>	0.05		<i>E_FR_DD_QLF</i>	0.092	<i>E_FR_DD_percent</i>	43%
<i>agg_v_max*</i>	38.5M		<i>E_FR_DD_QLF_A</i>	0.085	<i>E_FR_DD_percent_A</i>	48%
<i>v_min_A</i>	0.95		<i>E_FR_DD_QLF_B</i>	0.100	<i>E_FR_DD_percent_B</i>	47%
<i>v_min_B</i>	0.9		<i>E_FR_DD_QLF_C</i>	0.099	<i>E_FR_DD_percent_C</i>	44%
<i>v_min_C</i>	0.85		<i>E_FR_DD_QLF_D</i>	0.089	<i>E_FR_DD_percent_D</i>	40%
<i>v_min_D</i>	0.85		<i>AbsChurn_DU_QLF</i>	109,746	<i>Churn_percent</i>	0.65%
<i>p_up_A</i>	1		<i>AbsChurn_DU_QLF_A</i>	1,479,288	<i>Churn_percent_A</i>	1.13%
<i>p_up_B</i>	1		<i>AbsChurn_DU_QLF_B</i>	694	<i>Churn_percent_B</i>	0.24%
<i>p_up_C</i>	1		<i>AbsChurn_DU_QLF_C</i>	0.251	<i>Churn_percent_C</i>	0.79%
<i>p_up_D</i>	1		<i>AbsChurn_DU_QLF_D</i>	2.848	<i>Churn_percent_D</i>	0.70%
<i>p_down_A</i>	1					
<i>p_down_B</i>	1					
<i>p_down_C</i>	1					
<i>p_down_D</i>	1					

* The order of magnitude for *agg_v_max* is million.

The output of WIOM-ERP using the NAVSUP WSS input values results in a higher overall percentage of items that deviate from their target fill rate (both globally or in each *band*) than the percentage of items that deviate from their target churn of zero. Cross comparison between fill rate and absolute-churn QL MOPs is not performed because the units of those MOPs are different.

It is important to note that the objective of the WIOM-ERP optimizer is to minimize the deviation of fill rate and churn from the target value for each item regardless of their units. We use two different types of MOPs to facilitate our understanding of the system. PID MOP values describe the expected number of items that deviate from their target, but

contain no information about the magnitude of the variations that may occur. QL MOP values involve a potential tradeoff between the mean performance and the consistency of that performance—a minimal loss configuration must simultaneously achieve expected outcomes near the target and do so with low variability. Increases in QL MOP measures can be due to increased expected deviations from target, increased volatility, or both.

B. MOP RESPONSE TO FACTOR VARIATIONS

In this section, we develop statistical metamodels using DOE along with multiple regression and partition analysis to evaluate the influence each of the factors explored has on the MOP. Descriptive metamodels yield insight into how the MOPs are influenced by the variations in the factors. In other words, the MOPs are the response variables and the factors are the explanatory variables in the metamodels.

Each of the 14 factors that we identified in Table 1 is considered a potential main effect in our metamodel development. To explore possible interactions between the factors and non-linearity in the response surface of the MOPs, we also incorporate two-way interaction terms and a variety of non-linear alternatives in our metamodel development. We identify the most significant terms with the proper transformations in the following four-step process for metamodel development:

1. Choose the MOP and the terms for the initial regression: the original 14 factors from Table 1, two-way interactions, and other non-linear terms. Perform stepwise regression to reduce the number of terms. This is accomplished by eliminating those terms that have low information content relative to the MOP (i.e. low likelihood to predict it), as indicated by Bayes Information Criteria.
2. Using multivariate plotting, observe the shape of the data in the plot for the MOP relative to each factor. Identify any observable patterns that would indicate a need for alternative or additional data transformations for either that factor or the MOP. If a pattern has been identified, apply the data transformations to create new terms and repeat Step 1; otherwise, proceed to Step 3.

3. Identify potential lack-of-fit between the metamodel with and without the additional terms (from data transformations in Step 2). To do that, use the *R-square* and the *studentized residual* plot. If there are significant improvements to the *R-square* and residuals, keep the transformations; otherwise, revert to the model without the transformation.
4. Select the final terms for the metamodel, for each MOP, as those that have high statistical predictive power (small *p-value*). In addition, eliminate terms that have less “practical” significance based on subjective judgment such as *t-ratio* being substantially less than the highest *t-ratio*.

In Step 3, we note that “The Studentized Residual by Row Number plot essentially conducts a *t-test* for each residual” (SAS 2018).

In Step 4, we note that with JMP’s multiple regression tool all included terms are statistically significant (as indicated by a small *p-value*). Recall that statistical significance is strongly determined by sample size, and the designs we are using provide very large sample sizes. Furthermore, the number of potential terms in the metamodel is large, so there are likely to be several false positive identifications given a default value of $\alpha = 0.05$. Thus, we assess practical importance using the *sorted parameter estimate* list generated by JMP, which orders the relative sensitivity of the MOP to the *parameter estimates* based on their *t-ratios*. For our descriptive analysis, we consider a term practically insignificant when the *t-ratio* of that term is substantially less than that of the highest *t-ratio* in the metamodel and eliminating the term has “minimal” impact on *R-square*. Eliminating such terms creates a more parsimonious metamodel based solely on the dominant effects.

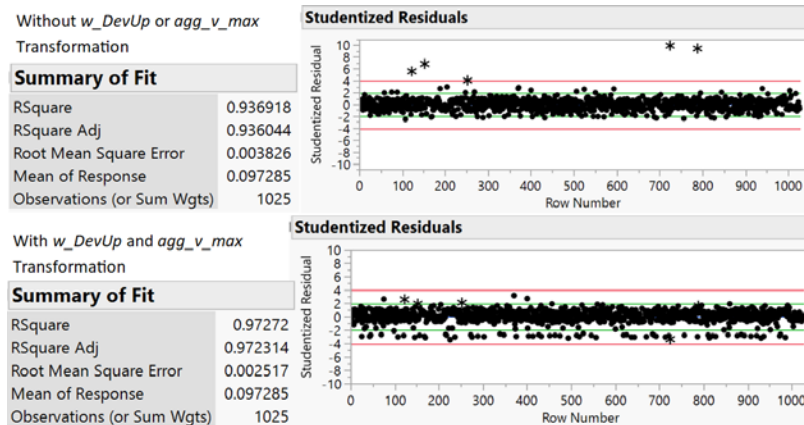
It is important to note that these metamodels are not used for the prediction of WIOM-ERP outcomes, but rather are descriptive and provide insights into the effects of input variation on the output of WIOM-ERP. We analyze the data globally and by *band* in both fill rate and churn categories for the QL and PID MOPs in the following sections of this chapter.

1. Global MOPs

As explained in Chapter II, we have formulated four global MOPs: expected fill rate deviation down quadratic loss function, $E_{FR_DD_QLF}$; percentage of items that deviate down from the target fill rate, $E_{FR_DD_percent}$; absolute churn deviation up quadratic loss function, $AbsChurn_DU_QLF$; and, percentage of items that incur churn, $Churn_percent$. The following are the descriptive metamodels that we use to analyze the effects of factor variation on each.

a. QL MOP for Global Fill Rate

In Step 1 of our metamodel development for $E_{FR_DD_QLF}$, we achieve an *R-square* of 0.94. However, there are five outliers indicated by “*” in the first studentized plots of Figure 2. In Step 2, we determine that the common element for the outlier datapoints is when the factor w_DevUp has a value of 0.00001 while agg_v_max is at its lower limit. We use a reciprocal transformation on w_DevUp and a logarithmic transformation of agg_v_max , then regenerate the model using the stepwise tool as discussed in Step 1.



The datapoints designated by “*” are the outliers. Using the reciprocal transformation of w_DevUp and logarithmic transformation of agg_v_max factors significantly improves the metamodel.

Figure 2. $E_{FR_DD_QLF}$ model residuals comparison

The comparison in Step 3 is between the two summaries of fit in Figure 2, and it indicates that the reciprocal transformation of w_DevUp and logarithmic transformation of agg_v_max in the metamodel for $E_FR_DD_QLF$ make significant improvements over the non-transformed factors. Based on these results we continue to Step 4 with the transformed factors in the metamodel.

We use the sorted parameter estimate list shown in Figure 3 and do not identify terms we consider to be practically insignificant due to their t-ratio values compared to the most influential parameter estimator. The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the $E_FR_DD_QLF$ MOP are shown in Figure 3 along with the sorted parameter estimates.

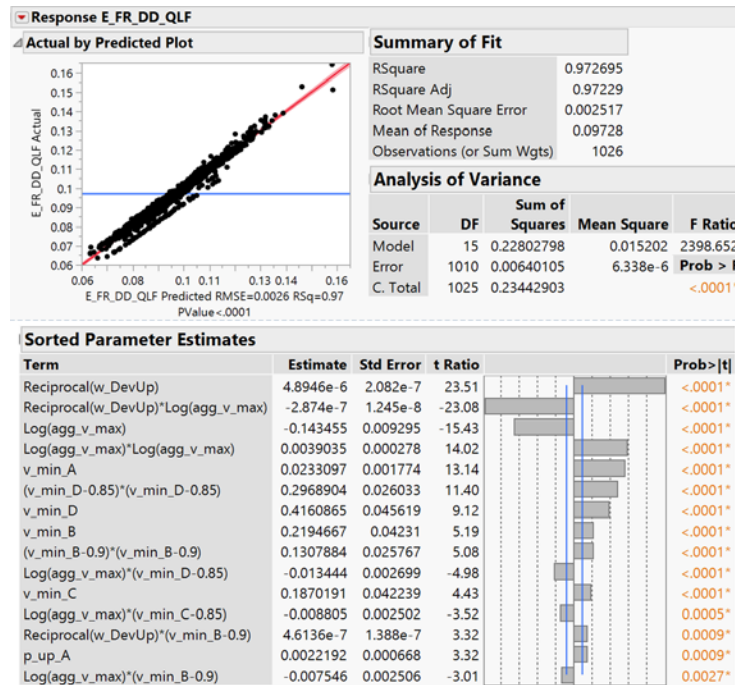


Figure 3. $E_FR_DD_QLF$ metamodel

The metamodel in Figure 3 helps us describe the sensitivity of the global fill rate magnitude of deviation below the target fill rate (QL MOP for global fill rate) with respect to the changes in the input values of w_DevUp , agg_v_max , minimum fill rate target

v_{min_A} through D , and p_{up_A} . The QL MOP for global fill rate is most sensitive to the weight of the global churn deviation and the Budget constraint agg_v_max .

As the budget decreases, the likelihood of items deviating further from the target fill rate increases. Changing the weight of the global churn deviation w_DevUp does not have a significant effect on the QL MOP for global fill rate. As each *band*'s minimum fill rate target values increase, the QL MOP for global fill rate increases because WIOM-ERP PMSS level recommendations are less likely to meet the higher target fill rates. The QL MOP for global fill rate is also slightly sensitive to the churn penalty scale factor in *band A*.

When w_DevUp is near zero the effects of the budget constraint become more significant, as shown by the interaction plot in Figure 4. Significant interactions are indicated when the plots corresponding to opposite extremes of the interacting variables are not parallel to each other.

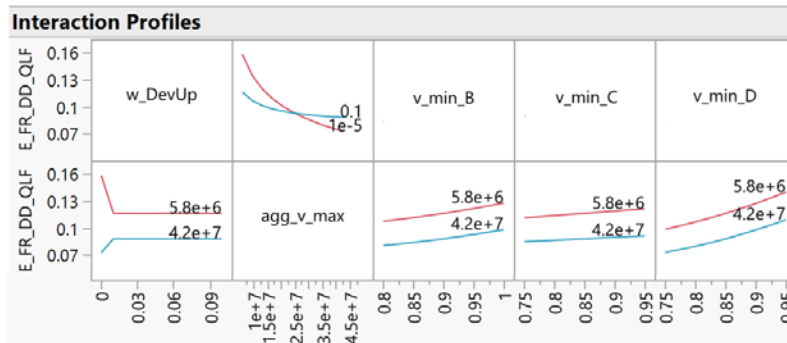
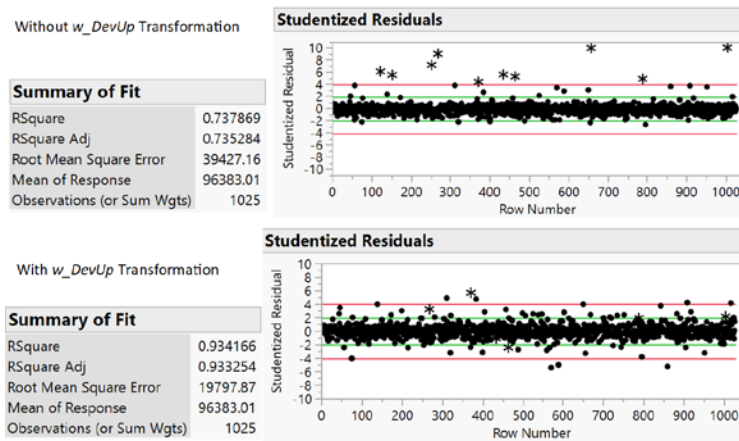


Figure 4. Interaction influence of factors on $E_FR_DD_QLF$

The interaction plot in Figure 4 highlights how fill rate is affected when both churn weight (w_DevUp) and budget (agg_v_max) are at their lowest limits. The fill rate is presumed to improve when giving less importance to churn (by decreasing the weight of the global churn in the objective function.) But, at the lowest budget limit (\$58M), the fill rate increases when the churn weight decreases. This counter-intuitive effect could be explained by the fact that our MOPs are not identical to the ones being optimized, or it may be due to the existence of multiple optimal solutions.

b. QL MOP for Global Churn

In Step 1 of our metamodel development for *AbsChurn_DU_QLF*, we achieve an *R-square* of 0.74; however, there are ten outliers indicated by “*” in the first studentized plots of Figure 5. In Step 2, we determine that the common element for the outlier datapoints is when the factor *w_DevUp* has a value of 0.00001. We use a logarithmic transformation on *w_DevUp* and regenerate the model using the stepwise tool as discussed in Step 1.



The datapoints designated by “*” are the outliers. Using the logarithmic transformation of *w_DevUp* factor significantly improve the metamodel.

Figure 5. *AbsChurn_DU_QLF* model residuals comparison

The comparison in Step 3 is between the two summaries of fit in Figure 5 and it indicates that the reciprocal transformation of *w_DevUp* in the metamodel for *AbsChurn_DU_QLF* makes a significant improvement over the non-transformed factor. Based on these results we continue to Step 4 with the transformed factor in the metamodel.

In Step 4, we use the sorted parameter estimate list shown in Figure 6 and do not identify terms we consider to be practically insignificant. The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the *AbsChurn_DU_QLF* MOP are shown in Figure 6.

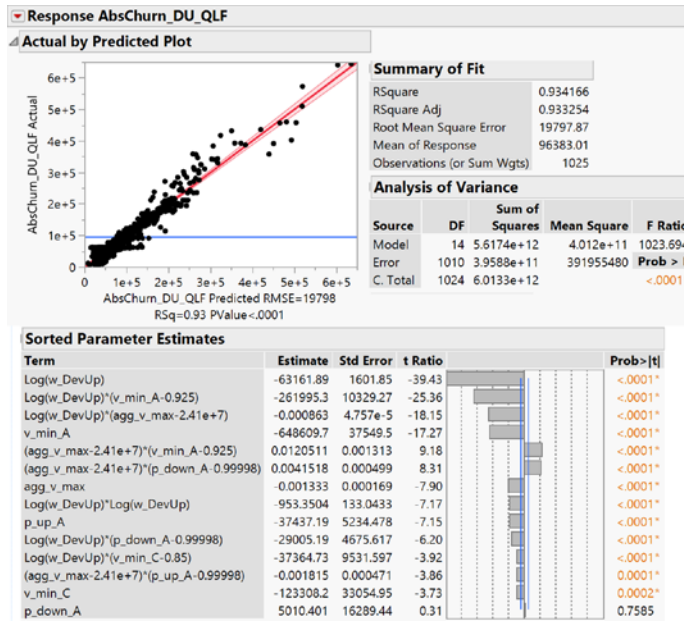
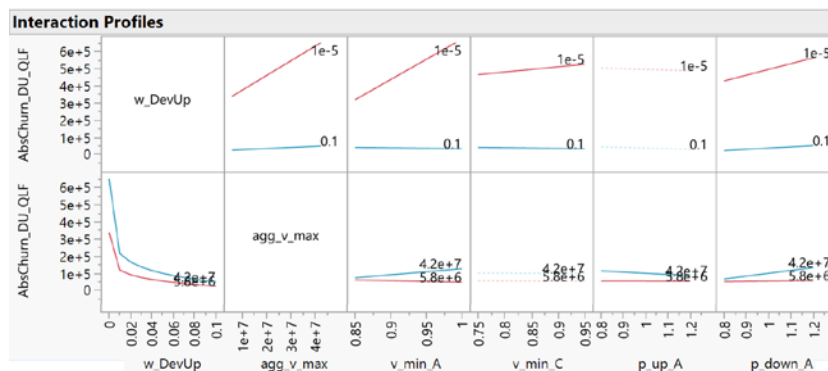


Figure 6. *AbsChurn_DU_QLF* metamodel

The metamodel in Figure 6 helps us describe the variation of the global churn magnitude of deviation from zero (QL MOP for global churn) with respect to the changes in the input values of w_DevUp , agg_v_max , v_min_A , p_up_A , v_min_C , and p_down_A in the order of sensitivity. The interaction effects of these input values are shown in Figure 7, and the curvature of the lines indicate non-linearity of the response surface with respect to the factors.



The solid lines indicate strong interaction between the factors, and the dotted lines indicate insignificant interactions between the factors.

Figure 7. Interaction influence of factors on *AbsChurn_DU_QLF*

Changing the weight of the global churn deviation w_{DevUp} has the most significant effect on the QL MOP for global churn. Increasing the w_{DevUp} value gives more importance to minimizing the churn deviation for each item and decreases the global churn. The QL MOP for global churn is slightly sensitive to the budget constraint agg_v_max . However, when w_{DevUp} is near zero the effects of the budget constraint become more significant as shown by the interaction plot in Figure 7.

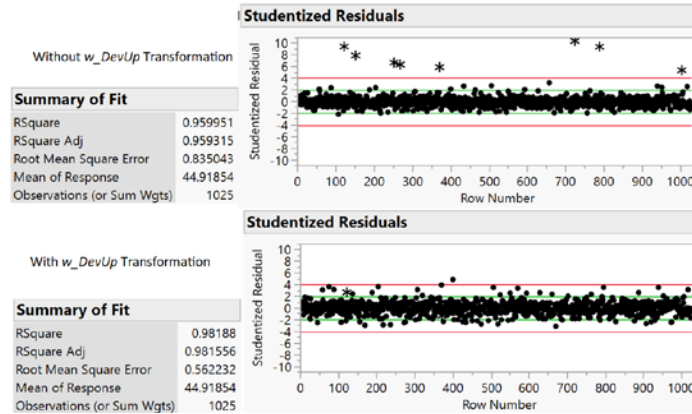
Global churn decreases slightly when the budget decreases. The budget constraint agg_v_max also interacts with v_min_A , p_up_A , and p_down_A , which implies that decreasing the budget has the most significant tradeoff between fill rate and churn in *band A*. This implies that global churn is driven by churn in *band A*.

Global churn is also sensitive to minimum fill rate target v_min_A and the scale factor for the fill rate deviation penalty in *band A* p_down_A . The interaction plot in Figure 7 indicates that at lower values of w_{DevUp} the tradeoff between churn and fill rate becomes very significant in *band A*. This tradeoff is also observed for *band C*, but it is much less significant, as indicated by v_min_C .

The scale factors for churn deviation penalty in *bands B, C, and D* do not have any effect on minimizing the global churn; only in *band A*, increasing the p_up_A value has small effect on decreasing the global churn. The metamodel also implies that churn in *band A* accounts for most of the global churn.

c. PID MOP for Global Fill Fate

In Step 1 of our metamodel development for $E_FR_DD_percent$, we achieve an *R-square* of 0.96; however, there are five outliers indicated by “*” in the first studentized plots of Figure 8. In Step 2, we determine that the common element for the outlier datapoints is when the factor w_{DevUp} has a value of 0.00001. We use a reciprocal transformation on w_{DevUp} and regenerate the model using the stepwise tool as discussed in Step 1.



The datapoints designated by “*” are the outliers. Using the reciprocal transformation of w_{DevUp} factors significantly improves the metamodel.

Figure 8. $E_{FR_DD_percent}$ model residuals comparison

The comparison in Step 3 is between the two summaries of fit in Figure 8 and it indicates that the reciprocal transformation of w_{DevUp} in the metamodel for $E_{FR_DD_percent}$ makes a significant improvement over the non-transformed factors. Based on these results we continue to Step 4 with the transformed factor in the metamodel.

In Step 4, we use the sorted parameter estimate list shown in Figure 9 to identify terms we consider to be practically insignificant due to their lower t -ratios.

Term	Estimate	Std Error	t Ratio	Prob> t
v_min_D	50.363747	0.297394	169.35	<.0001*
v_min_B	30.954501	0.297453	104.07	<.0001*
agg_v_max	-1.39e-7	1.636e-9	-84.98	<.0001*
(agg_v_max-2.41e+7)*(agg_v_max-2.41e+7)	7.195e-15	1.74e-16	41.24	<.0001*
v_min_A	14.577397	0.396302	36.78	<.0001*
v_min_C	9.44018	0.297303	31.75	<.0001*
Reciprocal(w_DevUp)*(agg_v_max-2.41e+7)	-2.84e-12	1.45e-13	-19.62	<.0001*
(v_min_B-0.9)*(v_min_B-0.9)	109.6313	5.744801	19.08	<.0001*
(v_min_D-0.85)*(v_min_D-0.85)	101.70089	5.853116	17.38	<.0001*
p_down_D	2.4731468	0.148682	16.63	<.0001*
(v_min_A-0.925)*(v_min_A-0.925)	113.41593	10.23946	11.08	<.0001*
p_down_B	0.9904316	0.148633	6.66	<.0001*
Reciprocal(w_DevUp)	0.0012629	0.000198	6.37	<.0001*
Reciprocal(w_DevUp)*Reciprocal(w_DevUp)	-1.225e-8	1.981e-9	-6.18	<.0001*
(v_min_C-0.85)*(v_min_C-0.85)	35.316912	5.775757	6.11	<.0001*
(v_min_D-0.85)*(p_down_D-0.99998)	10.730893	2.493646	4.30	<.0001*
(v_min_B-0.9)*(p_down_B-0.99998)	7.7229199	2.499161	3.09	<.0021*
p_up_A	0.4292363	0.148715	2.89	0.0040*

The terms crossed out with a line have t -ratios values of less than seventeen. Other terms with small practical significance must remain in the model because they have higher-order terms that are statistically significant.

Figure 9. $E_{FR_DD_percent}$ practical significance determination of parameter estimates

The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the $E_{FR_DD_percent}$ MOP are shown in Figure 10 along with the sorted parameter estimates.

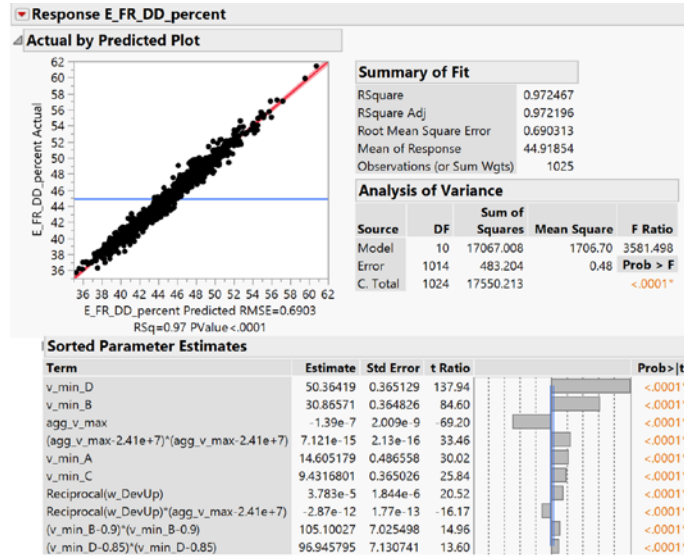


Figure 10. $E_{FR_DD_percent}$ metamodel

The metamodel in Figure 10 helps us describe the sensitivity of the global percent of items with deviation below target fill rate (PID MOP for global fill rate) with respect to the changes in the input values of minimum fill rate target v_{min_A} through D . As each *band*'s minimum target fill rate values increase, the PID MOP for global fill rate increases because WIOM-ERP PMSS level recommendations are less likely to meet the higher target fill rates. The order of sensitivity to each *band*'s minimum fill rate target as shown in the sorted parameter estimates also corresponds to the number of items in that *band* except for *bands A* and *C*. This exception can be attributed to *band A* average target fill rate of 0.95 and *band C* average target fill rate of 0.85. In other words, more items in the *band* correspond to higher PID MOP for global fill rate if the average target fill rates are the close. *Band D* has 2,018 items with 0.85 average target fill rate, *B* has 842 items with 0.90, *C* has 379 items with 0.85, and *A* has 266 items with 0.95.

The PID MOP for global fill rate is also sensitive to the Budget constraint agg_v_max . As the budget decreases, the likelihood of items deviating below the target fill rate increases. Changing the weight of the global churn deviation w_DevUp does not have a significant effect on the PID MOP for global fill rate. However, when w_DevUp is near zero the effects of the budget constraint become more significant as shown by the non-parallel plots in the interaction plot in Figure 11.

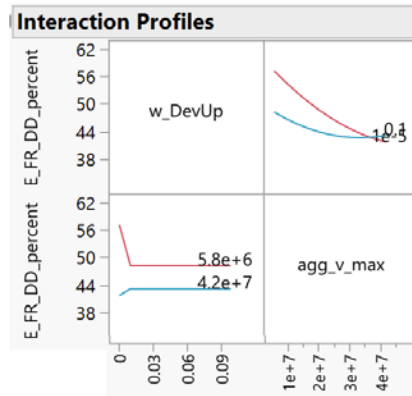
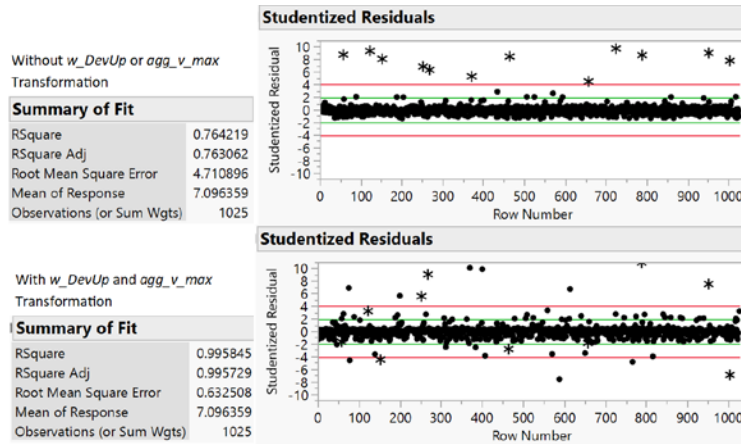


Figure 11. Interaction influence of factors on $E_FR_DD_percent$

d. PID MOP for Global Churn

In Step 1 of our metamodel development for $Churn_percent$, we achieve an R -square of 0.76; however, the datapoints indicated by “*” in the first studentized plots of Figure 12 do not satisfy the normality of error assumption for regression. In Step 2, we determine that the common element for the outlier datapoints is when the factor w_DevUp has a value of 0.00001. We use a reciprocal transformation on w_DevUp and a logarithmic transformation of agg_v_max by observing the pattern of the multivariate plot, then regenerate the model using the stepwise tool as discussed in Step 1.



The datapoints designated by “*” are skewed. Using the reciprocal transformation of w_DevUp and logarithmic transformation of agg_v_max factors significantly improves the metamodel by normalizing the residuals.

Figure 12. *Churn_percent* model residuals comparison

The comparison in Step 3 is between the two summaries of fit in Figure 12, and it indicates that the reciprocal transformation of w_DevUp and logarithmic transformation of agg_v_max in the metamodel for *Churn_percent* satisfy the regression assumption of normalized residuals. Based on these results we continue to Step 4 with the transformed factors in the metamodel.

In Step 4, we use the sorted parameter estimate list shown in Figure 13 to identify terms that we consider to be practically insignificant due to their relatively low *t-ratio* values.

Sorted Parameter Estimates				
Term	Estimate	Std Error	t Ratio	Prob> t
Log(agg_v_max)	-336.6009	2.32318	-144.9	<.0001*
Log(agg_v_max)*Log(agg_v_max)	9.6559505	0.069594	138.75	<.0001*
Reciprocal(w_DevUp)	0.010034	0.000272	36.83	<.0001*
Reciprocal(w_DevUp)*Log(agg_v_max)	-0.000291	9.525e-6	-30.52	<.0001*
Reciprocal(w_DevUp)*(v_min_C-0.85)	-0.002617	9.084e-5	-28.81	<.0001*
Reciprocal(w_DevUp)*(p_down_C-0.99998)	0.0006658	0.000026	25.69	<.0001*
Reciprocal(w_DevUp)*(p_down_B-0.99998)	0.0005006	1.986e-5	25.21	<.0001*
Reciprocal(w_DevUp)*Reciprocal(w_DevUp)	-4.819e-8	2.212e-9	-21.79	<.0001*
Reciprocal(w_DevUp)*(p_up_C-0.99998)	0.0007432	3.568e-5	20.83	<.0001*
Reciprocal(w_DevUp)*(v_min_B-0.9)	-0.003092	0.000152	-20.40	<.0001*
Reciprocal(w_DevUp)*(p_up_B-0.99998)	0.0006652	3.325e-5	20.01	<.0001*
Reciprocal(w_DevUp)*(p_up_A-0.99998)	-0.001143	0.000062	-18.47	<.0001*
Reciprocal(w_DevUp)*(v_min_A-0.925)	0.0006811	3.942e-5	17.28	<.0001*
Reciprocal(w_DevUp)*(v_min_D-0.85)	-0.000648	5.553e-5	-11.67	<.0001*
Reciprocal(w_DevUp)*(p_up_D-0.99998)	-0.00028	0.00003	-9.32	<.0001*
p_down_A	0.5681479	0.168129	3.38	0.0008*
(p_up_A-0.99998)*(p_up_B-0.99998)	-4.507874	1.444433	-3.12	0.0019*
Reciprocal(w_DevUp)*(p_down_A-0.99998)	-0.000112	0.000044	-2.54	0.0111*
p_up_B	-0.292842	0.168893	-1.73	0.0832
p_up_C	-0.267555	0.168443	-1.59	0.1125
v_min_B	0.2744755	0.336467	0.82	0.4148
v_min_C	-0.169829	0.335932	-0.51	0.6133
p_up_D	-0.059733	0.168356	-0.35	0.7228
p_down_C	0.0568864	0.168312	0.34	0.7354
p_down_B	-0.050897	0.168806	-0.30	0.7631
p_up_A	0.0466527	0.16839	0.28	0.7818
v_min_A	0.1035849	0.449954	0.23	0.8180
v_min_D	-0.045459	0.337604	-0.13	0.8929

The terms crossed out with a line have t-ratios values of less than fifteen. Other terms with small practical significance must remain in the model because they have higher-order terms that are statistically significant.

Figure 13. *Churn_percent* practical significance determination of parameter estimates

The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the *Churn_percent* MOP are shown in Figure 14 along with the sorted parameter estimates.

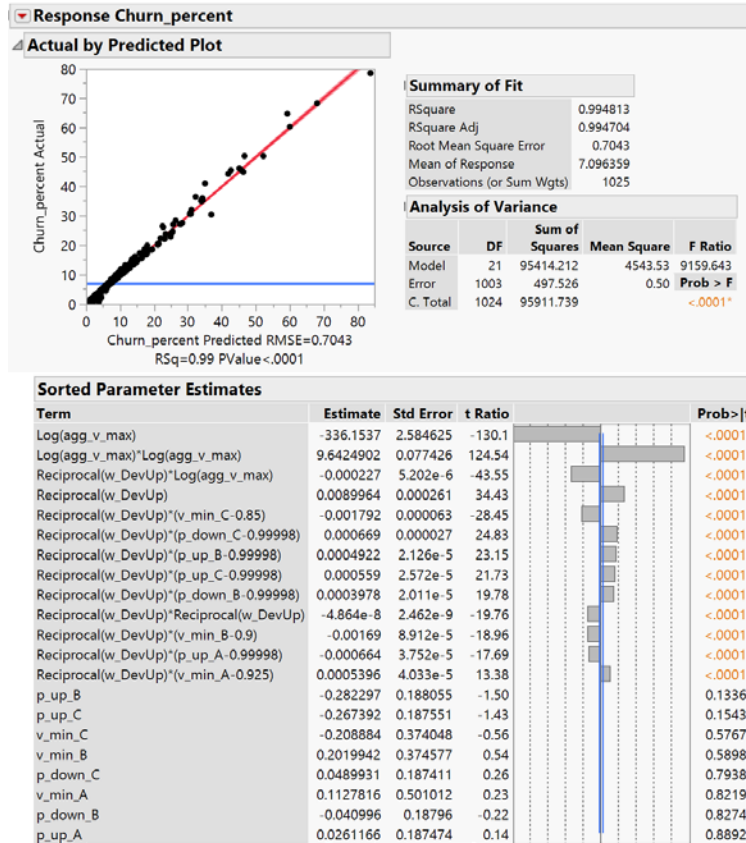
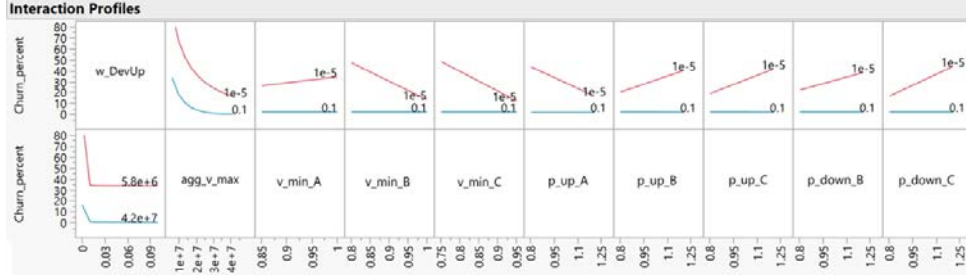


Figure 14. *Churn_percent* metamodel

The metamodel shown in Figure 14 helps us describe the sensitivity of the global percent of items with deviation from zero churn (PID MOP for global churn) with respect to the changes in the input value of *agg_v_max*. Decreasing the budget constraint enforces a decrease in PMSS levels globally which can cause churn in more items.

PID MOP for global churn is also sensitive to *w_DevUp*. As the *w_DevUp* value increases from near zero to less than 0.02, there is a rapid decline in the number of items where churn is observed. However, for values of *w_DevUp* greater than 0.02, the decline in the number of items with churn becomes less significant. The response surface of PID MOP for churn is also sensitive to the interaction of *w_DevUp* with other input variables as shown in Figure 15.



The solid lines indicate a strong interaction between the factors, and the dotted lines indicate insignificant interactions between the factors.

Figure 15. Interaction influence of factors on *Churn_percent*

The interaction plot highlights the significant effect of p_up_B , p_up_C , v_min_C , v_min_B , p_down_C , v_min_A , p_down_B , and p_up_A on the response surface for the global churn PID MOP as w_DevUp gets closer to zero. In other words, when the weight of the global churn is minimum, the number of items with churn becomes increasingly sensitive to other input values listed above. The gradient of the curves in Figure 15 indicates the correlation between the global number of items with churn and the input values.

2. *Band MOPs*

In this section we analyze the data for *band A* through *D* MOPs. We use the same process that was detailed in the previous section to develop metamodels for each *band* MOP. Details of the *band*-specific MOP metamodels and their interaction plots are provided in the Appendix. We find that the global weight for churn deviation and the budget constraint are the most influential factors in the response surface of *band*-specific MOPs.

The descriptive metamodels that we use to analyze the effects of factor variation on QL and PID MOPs demonstrate that the fill rate in each *band* is most sensitive to the budget constraint and the target fill rate in that *band*. As each *band* minimum target fill rate value increases, the QL and PID MOPs for the fill rate in that *band* increase because WIOM-ERP PMSS level recommendations are less likely to meet the higher target fill rates. The QL and PID MOPs in each *band* for fill rate decrease as the budget constraint increases.

Changing the weight of the global churn deviation has the most significant effect on the QL MOP for churn in *band A*. Increasing the weight of the global churn deviation decreases the churn deviation in *band A* more significantly than other bands. Decreasing the budget decreases the QL MOP but increases the PID MOP for churn in *band A*. In other words, decreasing the budget causes a somewhat higher expected churn rate, but it also causes the churn deviation to be more consistently close to the target of zero in *band A*.

Besides the above-mentioned observations, the response surface of the QL and PID MOPs in other *bands* are similar to the global MOPs. Refer to the Appendix for further details about the *band*-specific MOP metamodels.

3. MOPs without Metamodels

We are unable to establish a metamodel for the churn QL MOP in *bands B* and *D*. This is due to the clustering that we observe in the data plot of the QL MOP for *AbsChurn_DU_QLF* in *bands B* and *D* when w_DevUp values are smaller than 0.01 as seen in Figure 16. We were unable to correlate the banding to any combination of inputs.

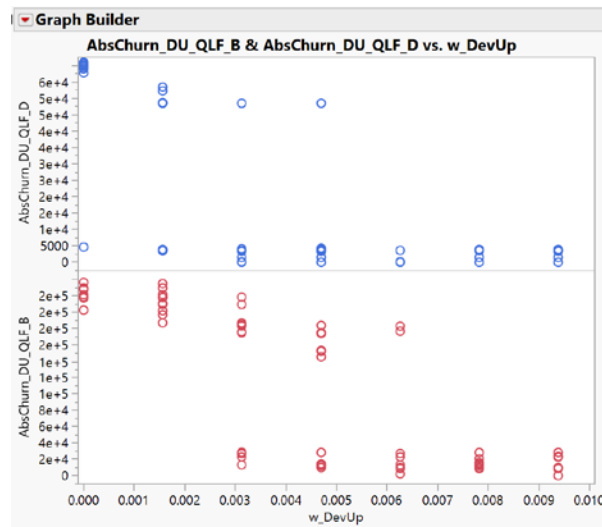


Figure 16. Clustering of QL MOP for churn in *band B* and *D*

One possible explanation is that there could be multiple PMSS levels that satisfy the objective function for churn in WIOM-ERP optimizer. Further investigation to identify the cause of this phenomenon is beyond the scope of this study.

As an alternate method to the four steps described in section B of Chapter III, we have used partition tree models to construct “decision trees.” Partition trees work by identifying locations where binary splits yield the greatest separation between the averages of the MOPs within the resulting pair of subsets. Leaf labels from the partition tree can be used as categorical variables to develop metamodels for QL MOPs for churn in band B and D that have cluster response surface based on the w_DevUp values. However, using this approach yields no improvements in the metamodels of these MOPs.

C. MOP TRENDS

We use the metamodels that we developed in the previous section to study the MOP trends with respect to the baseline values for each input variable. Figures 17 and 18 are the output profiles of each MOP based on the developed metamodels when input values are set to their baseline values.

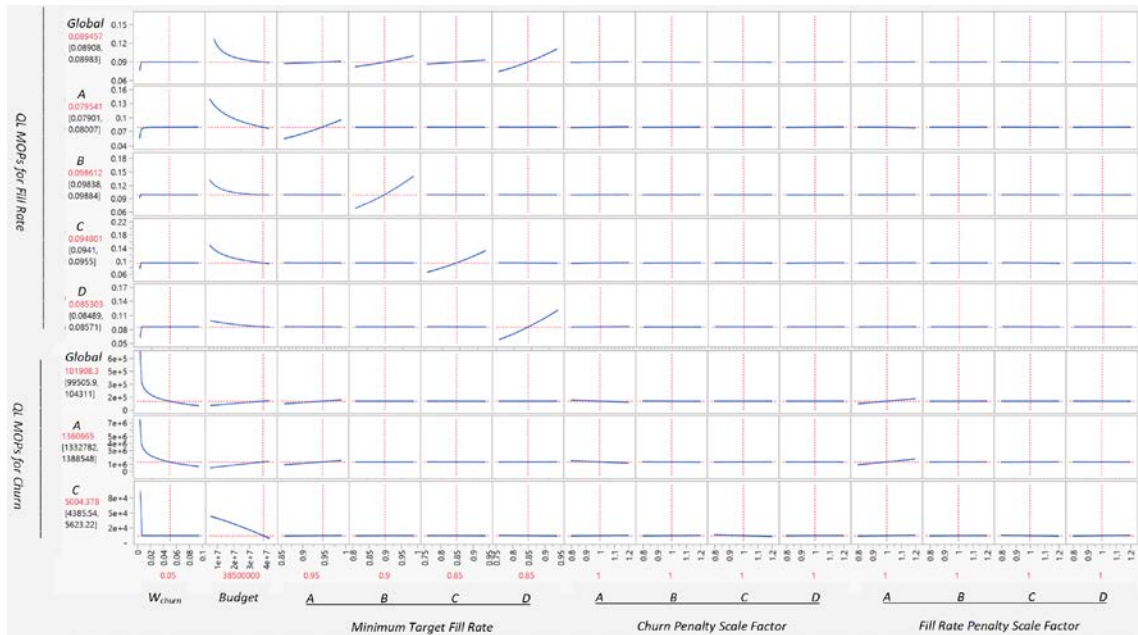


Figure 17. QL MOP metamodel trends

The most influential factors in QL MOPs are the global weight for churn and the budget constraint. Decreasing the global weight for churn does not have much effect on improving the fill rate globally and in all *bands*. However, that fill rate becomes more affected when the global weight for churn is less than 0.02. The global churn is driven by the churn in *band A*—both are affected by all values of global weight for churn across its entire practical range.

These trends validate Teter's (2018) research that churn can be reduced without sacrificing fill rate. However, that is true only for the consistency of churn performance when the weight of global churn is greater than 0.02. As displayed in Figure 17 and 18, increasing the weight of the global churn improves the QL MOP, but the PID MOP remains flat. That indicates a higher weight of global churn more consistently gets the item churn close to the target value without significantly decreasing the number of items with churn.

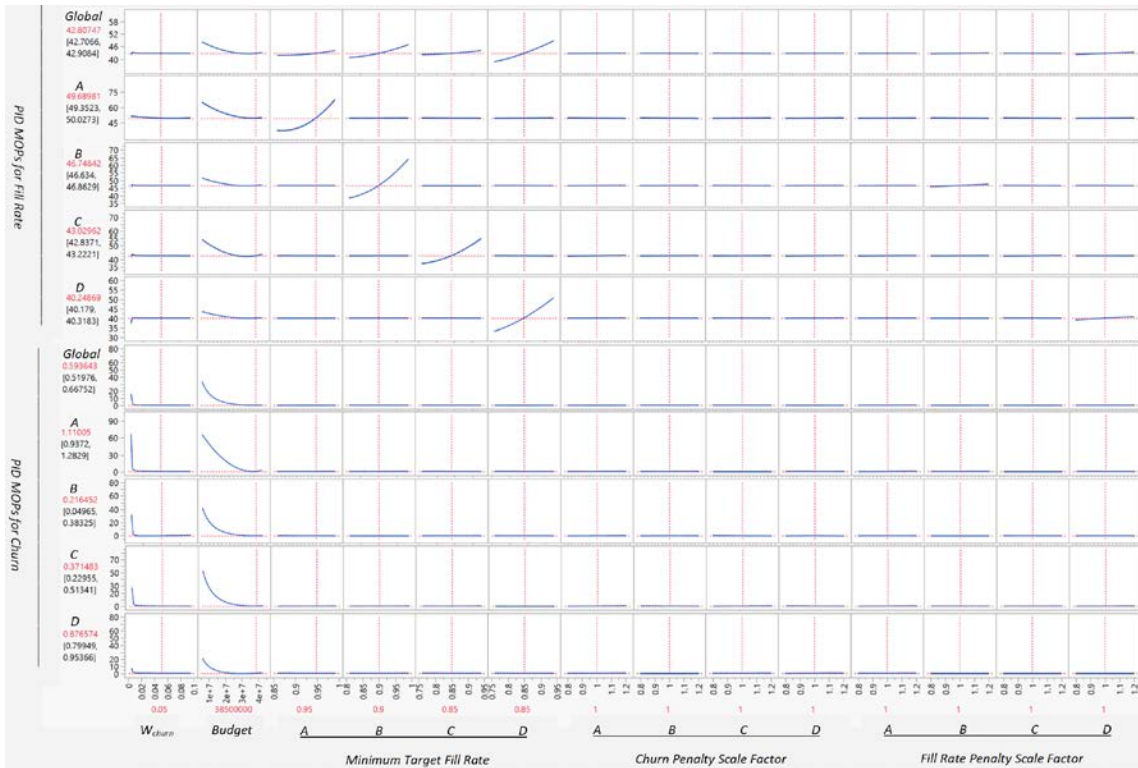


Figure 18. PID MOP metamodel trends

Comparing the QL and PID MOP for the global and *band A* churn concerning the budget constraint highlights that the QL MOP for churn slope is reversed. This reversal of slope indicates that increasing the budget constraint leads to a decrease in the expected number of items with churn, but it increases the expected loss from less consistently getting the items' churn close to the target value.

Increasing the target fill rate does not affect the churn, but it increases the number of items that deviate from their target fill rate. At baseline values of global weight for churn and budget, changing the penalty scale for churn and fill rate has no significant effect of churn or fill rate with the exception of fill rate penalty in *band A*. Increasing the fill rate penalty scale factor in *band A* increases the magnitude of churn deviation in *band A*, which increases the QL MOP for global churn.

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IV. CONCLUSIONS AND RECOMMENDATIONS

This thesis has used DOE to explore the effects of user input values in the WIOM-ERP, inventory optimization program used by NAVSUP WSS, on maritime, non-nuclear, consumable inventory. The data from our DOE have been used to calculate the fill rate and churn MOPs for both quadratic loss and percent of items with deviation. The metamodels that we have developed indicate that the most influential factors are the global weights and the budget constraint. In this chapter we summarize the fill rate and churn MOP's response surface based on our analysis from the metamodels.

A. GLOBAL WEIGHT AND BUDGET CONSTRAINT EFFECTS

As mentioned in Chapter II, we keep the value of the global weight for expected fill rate deviations below the target at a constant 1.0. Since this term appears in the objective function of the optimization, we can reproduce any other value by modifying the weight of the other objective terms (specifically the churn weight) as long as we maintain the relative ratio between them.

The metamodels in Chapter III reveal significant interaction effects between the churn weight and the budget constraint in QL and PID MOPs response surface for both churn and fill rate. In the maritime, non-nuclear, consumable database, the effects of the budget constraint on all MOP's response surfaces become more significant when the churn weight value is below 0.02. For values of churn weight from 0.02 to 0.1, the effects of churn weight on all MOPs is negligible.

The QL and PID MOPs for fill rate are most sensitive to the budget constraint. As the budget constraint decreases the QL and PID MOPs for fill rate increase, indicating that WIOM-ERP PMSS level recommendations are more likely to deviate from their target fill rate. Decreasing the churn weight to near zero leads to slight improvement in global fill rate, but it causes significant churn. This outcome validates Teter's (2018) research that churn can often be reduced without sacrificing fill rate.

The QL and PID MOPs for churn, with the exception of churn QL MOP in *band A*, show no sensitivity to churn weight values that are greater than 0.02. The QL MOP for

churn in *band A* decreases consistently as the churn weight value increases throughout its practical range. Given that the PID MOP remains relatively flat throughout most of the same range, we conclude that lower churn weight yield increasing volatility. The gradient of the QL MOP response surface becomes steeper for churn weight values less than 0.02. Since the response surface of QL MOP for global churn follows the same trend as churn in *band A* in response to changes of churn weight and budget constraint, we conclude that global churn is driven by churn in *band A*.

B. TARGET FILL RATE INPUT EFFECTS

The changes to the target fill rate inputs for each *band* primarily effect the fill rate MOPs. As each *band*'s minimum fill rate target values increase, the QL and PID MOPs for that *band* fill rate increase because WIOM-ERP PMSS level recommendations are less likely to meet the higher target fill rate in that *band*. The QL and PID MOPs for global fill rate are affected by the cumulative effects of each *band*'s target fill rate increase. Global fill rate PID MOP order of sensitivity to each *band*'s minimum target fill rate corresponds to the number of items in that *band*. In other words, having more items in the *band* corresponds to a higher PID in fill rate globally. *Band D* has 2,018 items, *B* has 842 items, *C* has 379 items, and *A* has 266 items.

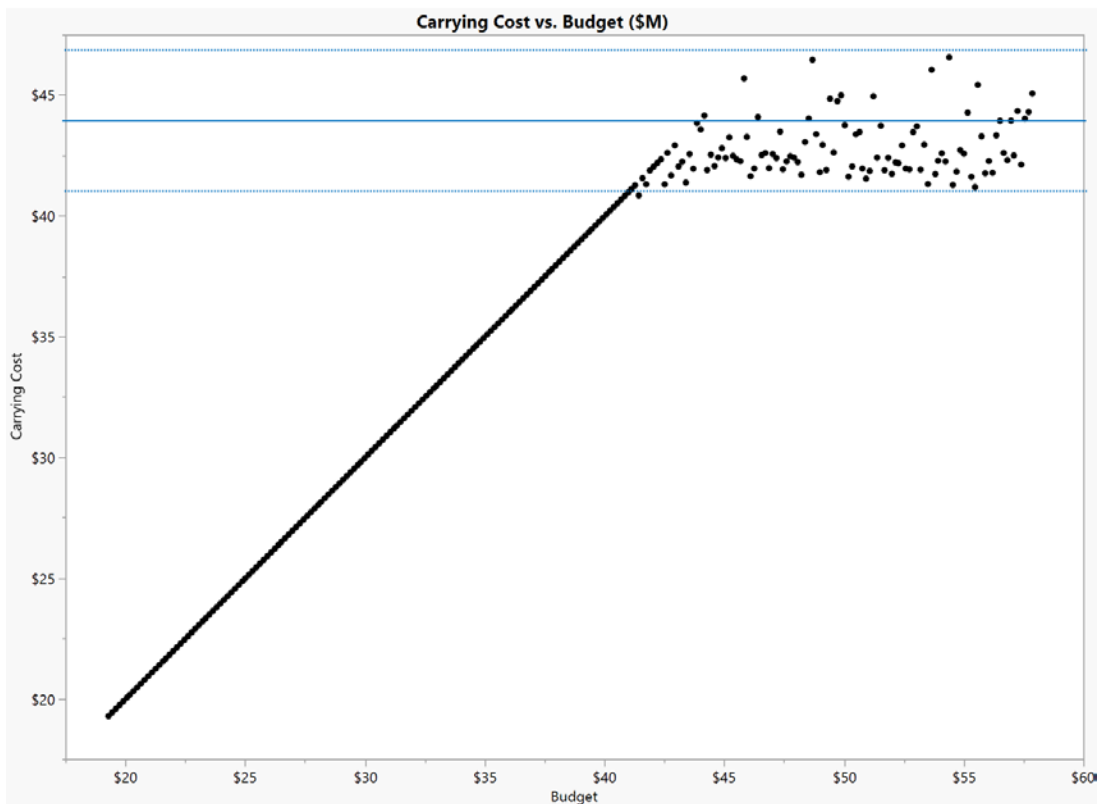
The churn MOPs are not sensitive to target fill rates. However, as the churn weight decreases to favor fill rate while the budget constraint is decreased, the churn MOPs sensitivity to target fill rate becomes more significant.

C. PENALTY SCALE FACTOR EFFECTS

We also observe the significance of the individual item fill rate and churn penalties scale factor increase only when churn weight shifts to favor the fill rate objective. In other words, with the user provided (baseline) values for churn weight and budget constraint, the changes in penalty scale factors have no significant effects. The interaction plots in Chapter III provide more details about the MOP's response surface changes as churn weight interacts with the penalty scale factors.

D. PMSS INVENTORY CARRYING COST

The inventory carrying cost of the recommended PMSS level is not one of our MOPs. However, it is noteworthy to mention that it does not exceed a certain amount for the maritime, non-nuclear, consumable database once the budget constraint achieves a certain threshold. Our preliminary exploration shows the plot of PMSS cost as a function of the budget constraint in Figure 19.



Carrying cost is the sum of WIOM-ERP recommended PMSS costs for all the items in the maritime, non-nuclear, consumable inventory.

Figure 19. PMSS Cost of Maritime, non-nuclear, consumable Inventory

We can observe from Figure 19 that the PMSS cost does not exceed the mid \$40M even when the budget constraint is increased up to \$60M. This observation can serve as a cost analysis to prevent setting an unnecessarily high inventory budget. This can be a symptom of the optimization not being able to consider PMSS values that were not

simulated. This can also serve to limit achievable fill rate targets, if sufficiently high PMSS values were not simulated. Studying the simulation model of WIOM-ERP is beyond the scope of this thesis.

E. RECOMMENDATIONS

The current WIOM-ERP objective function minimizes the expected deviation from the target fill rate and churn. As a potential alternate, we recommend incorporating objective terms to minimize the expected loss for fill rate and churn. The possible tradeoff is that a low loss configuration may have a slightly bigger expected deviation from the target, but it may have a lower probability of being far away from the target. In other words, the interpretation of quadratic loss tells us that while a particular solution might have a somewhat higher expected deviation rate than other solutions, this can be offset by being more consistently close to the target values.

F. FOLLOW-ON RESEARCH

DOE is a versatile technique for studying complex systems such as WIOM-ERP and its performance on NAVSUP's inventory planning. We recommend using it to understand the tradeoffs between metrics in other than the maritime, non-nuclear, consumable NAVSUP inventory or for measuring the performance of future iterations of inventory optimization systems.

WIOM-ERP currently optimizes the raw performance measures of the system. Future research could attempt optimizing quadratic loss instead, and contrast the two approaches.

APPENDIX. BAND SPECIFIC METAMODELS

This appendix provides the detailed metamodels for QL and PID MOPs for each *band*.

A. QL MOP FOR BAND A FILL RATE

The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the $E_FR_DD_QLF_A$ MOP are shown in Figure 20 along with the sorted parameter estimates.

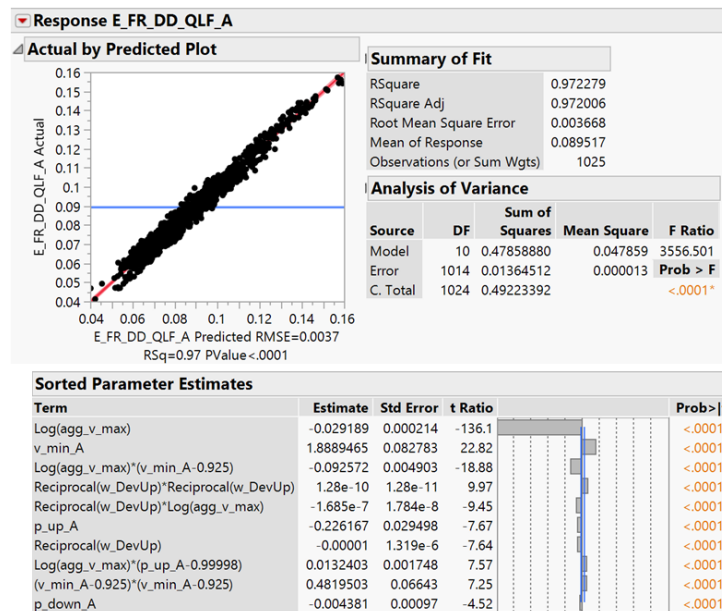


Figure 20. $E_FR_DD_QLF_A$ metamodel

The metamodel in Figure 20 helps us describe the sensitivity of the *band A* fill rate magnitude of deviation below the target fill rate (QL MOP for *band A* fill rate) with respect to the changes in the input values of budget agg_v_max , minimum fill rate target v_min_A , global churn weight w_DevUp , and scale factors for churn and fill rate in *band A*. Increasing the budget improves the fill rate in *band A*. As the *band A* minimum fill rate target value increases, the QL MOP for the *band A* fill rate increases because WIOM-ERP

PMSS level recommendations are less likely to meet the higher target fill rates in *band A*. The order of sensitivity to each input as shown in the sorted parameter estimates indicates that fill rate in *band A* is most sensitive to the budget.

The QL MOP for *band A* fill rate is also sensitive to the interaction between agg_v_max and w_DevUp as shown in Figure 21. When w_DevUp is near zero the effects of the budget constraint become more significant. There is also some sensitivity to interactions between w_DevUp and v_min_A , as well as p_up_A .

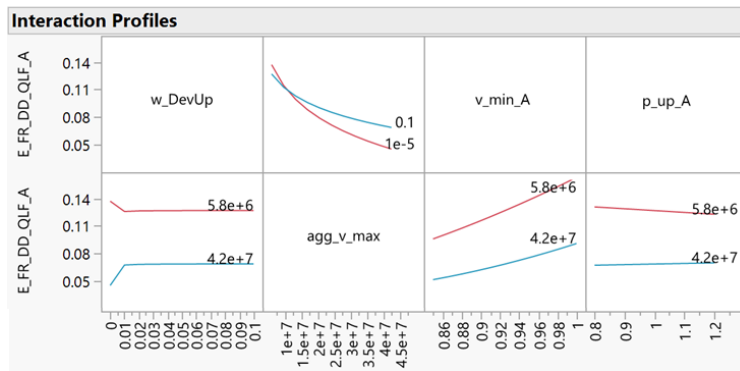


Figure 21. Interaction influence of factors on $E_FR_DD_QLF_A$

The metamodel of QL MOP for the *band A* fill rate highlights that the effects of the fill rate penalty scale factor p_down_A in *band A* are minimal.

B. QL MOP FOR BAND A CHURN

The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the $AbsChurn_DU_QLF_A$ MOP are shown in Figure 22.

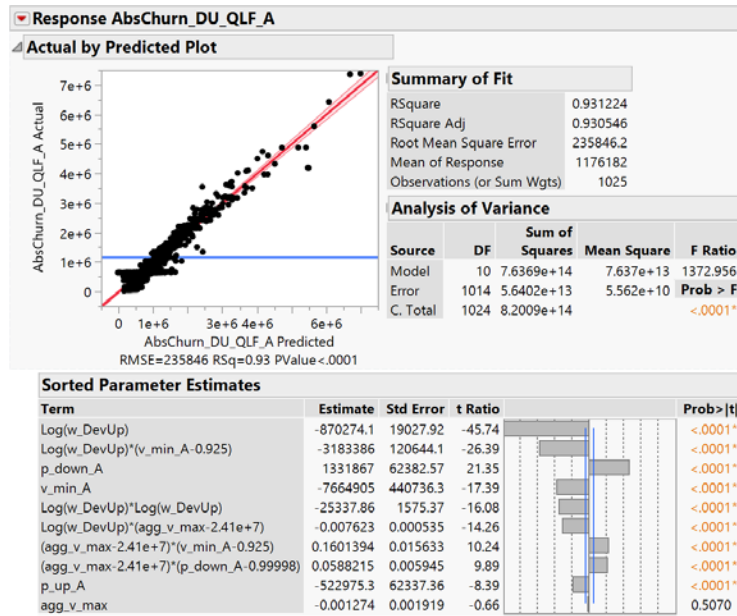


Figure 22. *AbsChurn_DU_QLF_A* metamodel

The metamodel in Figure 22 helps us describe the variation of the *band A* churn magnitude of deviation from zero (QL MOP for *band A* churn) with respect to the changes in the input values of w_DevUp , p_down_A , v_min_A , p_up_A , and agg_v_max in the order of sensitivity. Churn in *band A* decreases slightly when the budget decreases. The budget constraint agg_v_max also interacts with v_min_A , and p_down_A .

The interaction effects of these input values are shown in Figure 23, and the curvature of the lines indicate non-linearity of the response surface with respect to the factors.

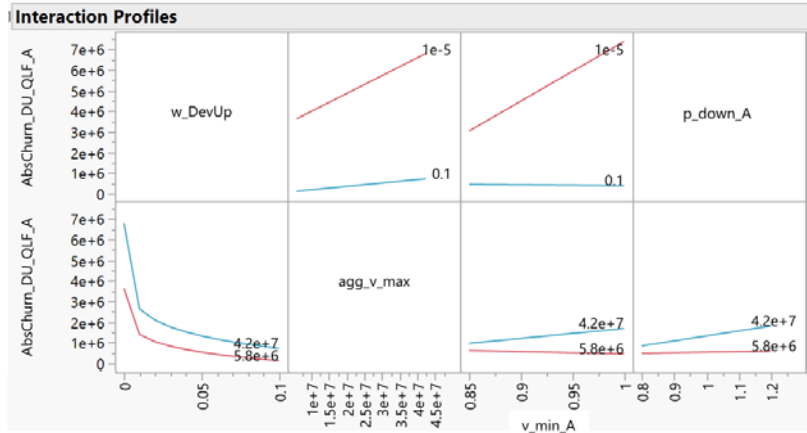


Figure 23. Interaction influence of factors on $AbsChurn_DU_QLF_A$

Changing the weight of the global churn deviation w_DevUp has the most significant effect on the QL MOP for *band A* churn. Increasing the w_DevUp value gives more importance to minimizing the churn deviation for each item and decreases the churn in *band A*. The QL MOP for global churn is less sensitive to the budget constraint agg_v_max than the interaction of agg_v_max with v_min_A and p_down_A .

C. PID MOP FOR BAND A FILL RATE

The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the $E_FR_DD_percent_A$ MOP are shown in Figure 24 along with the sorted parameter estimates.

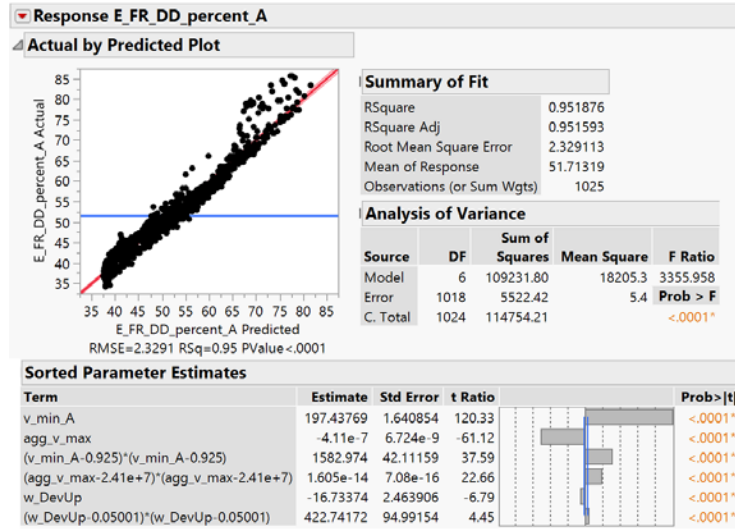


Figure 24. $E_FR_DD_percent_A$ metamodel

The metamodel in Figure 24 helps us describe the sensitivity of the *band A* percent of items with deviation below target fill rate (PID MOP for *band A* fill rate) with respect to the changes in the input values of v_min_A , agg_v_max , and w_DevUp . The PID MOP for *band A* fill rate is most sensitive to changes in *band A* minimum fill rate target value; increasing the target fill rate increases the number of items with deviations below target fill rate.

The PID MOP for *band A* fill rate is also sensitive to the Budget constraint agg_v_max . As the budget decreases, the likelihood of items deviating below the target fill rate increases in *band A*. Changing the weight of the global churn deviation w_DevUp does not have a significant effect on the PID MOP for *band A* fill rate. The PID MOP for *band A* fill rate is not affected by any factor interactions.

D. PID MOP FOR BAND A CHURN

The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the $Churn_percent_A$ MOP are shown in Figure 25 along with the sorted parameter estimates.

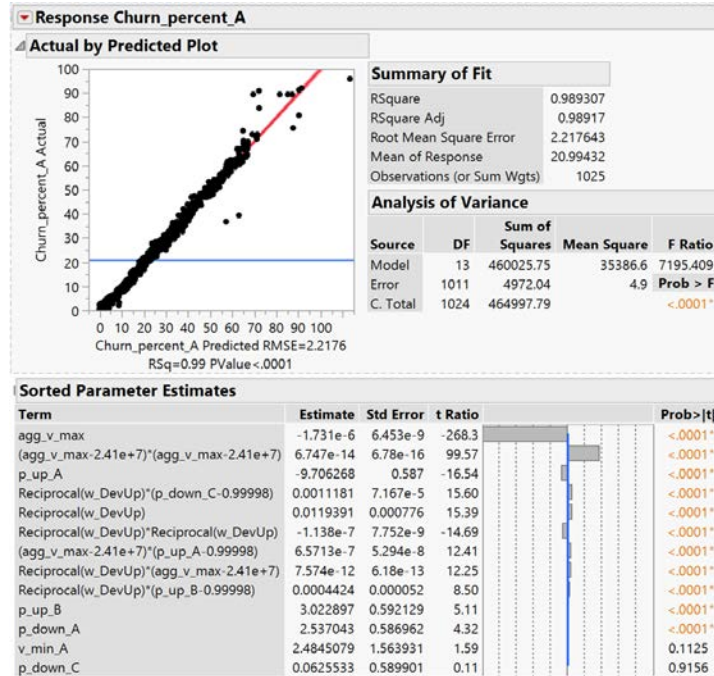


Figure 25. *Churn_percent_A* metamodel

The metamodel in Figure 25 helps us describe the sensitivity of the *band A* percent of items with deviation from zero churn (PID MOP for *band A* churn) with respect to the changes in the input value of *agg_v_max*. The quadratic form of the PID MOP for *band A* churn response surface indicates that minimum number of churns can be achieved at a certain budget constraint. The scale factor for fill rate penalty in *band A*, *p_down_A* has very small effect on the PID MOP for *band A* churn.

PID MOP for *band A* churn is also sensitive to *w_DevUp*. As *w_DevUp* value increases from near zero to less than 0.02, a rapid decline in the number of items with churn is observed. However, for values of *w_DevUp* greater than 0.02, the decline in the number of items with churn becomes less significant. The response surface of PID MOP for churn in *band A* is also sensitive to the interaction of *w_DevUp* with other input variables as shown in Figure 26.

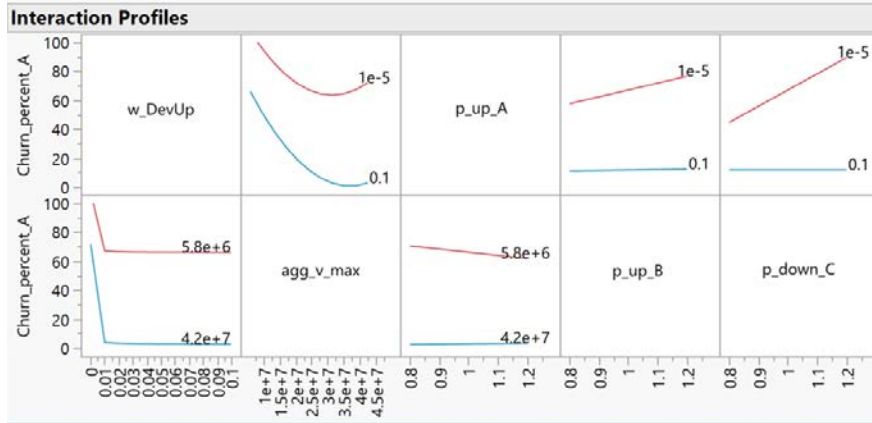


Figure 26. Interaction influence of factors on $Churn_percent_A$

The interaction plot highlights the significant effect of p_up_B and p_down_C on the response surface for PID MOP for *band A* churn as w_DevUp gets closer to zero. In other words, when the weight of the global churn is minimum, the number of items with churn in *band A* becomes increasingly sensitive to the penalty scale factors in *bands B* and *C* input values.

E. QL MOP FOR BAND B FILL RATE

The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the $E_FR_DD_QLF_B$ MOP are shown in Figure 27 along with the sorted parameter estimates.

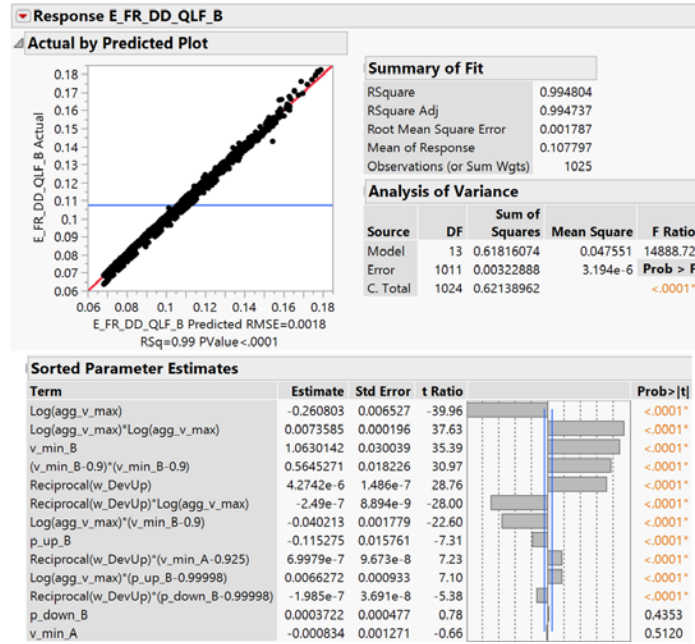


Figure 27. $E_{FR_DD_QLF_B}$ metamodel

The metamodel in Figure 27 helps us describe the sensitivity of the *band B* fill rate magnitude of deviation below the target fill rate (QL MOP for *band B* fill rate) with respect to the changes in the input values of budget agg_v_max , minimum fill rate target v_min_B , global churn weight w_DevUp , the scale factors for churn and fill rate in *band B*, and the minimum target fill rate for *band A* v_min_A . Increasing the budget improves the fill rate of items in *band B*. The order of sensitivity to each input as shown in the sorted parameter estimates indicates that fill rate in *band B* is most sensitive to the budget. The increase in target fill rate for *band A* decreases the fill rate in *band B*.

The QL MOP for *band B* fill rate is also sensitive to the interaction between agg_v_max and w_DevUp as shown in Figure 28. When w_DevUp is near zero the effects of the budget constraint become more significant. There is also some sensitivity to interactions between w_DevUp and v_min_A , p_down_B as well as agg_v_max and v_min_B , p_up_B factors.

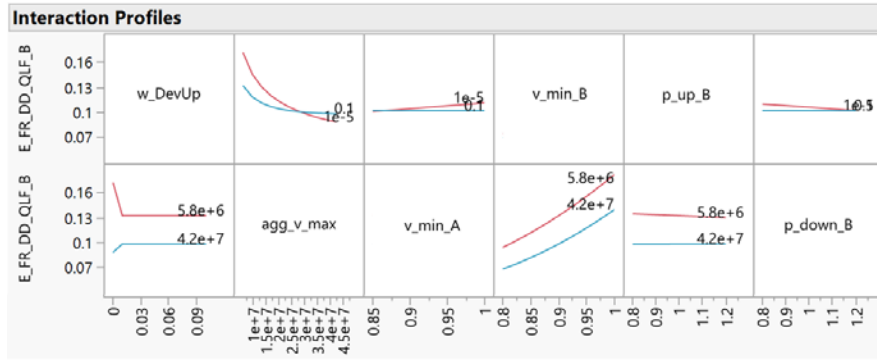


Figure 28. Interaction influence of factors on $E_{FR_DD_QLF_B}$

The metamodel of QL MOP for *band B* fill rate highlights that the effects of the penalty scale factors in *band B* are minimal on the fill rate in *band B*.

F. PID MOP FOR BAND B FILL RATE

The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the $E_{FR_DD_percent_B}$ MOP are shown in Figure 29 along with the sorted parameter estimates.

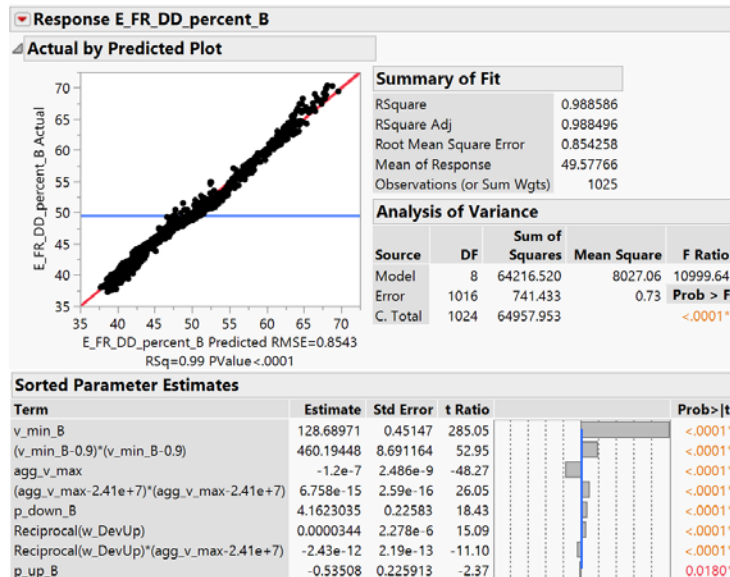


Figure 29. $E_{FR_DD_percent_B}$ metamodel

The metamodel in Figure 29 helps us describe the sensitivity of the *band B* percent of items with deviations below target fill rate (PID MOP for *band B* fill rate) with respect to the changes in the input values of v_{min_B} , agg_v_max , and w_DevUp . The PID MOP for *band B* fill rate is mostly sensitive to *band B* minimum target fill rate value.

The PID MOP for *band B* fill rate is also sensitive to the Budget constraint agg_v_max . As the budget decreases, the likelihood of items deviating below the target fill rate increases in *band B*. Changing the weight of the global churn deviation w_DevUp does not have a significant effect on the PID MOP for *band B* fill rate. However, when w_DevUp is near zero the effects of the budget constraint become more significant as shown by the interaction plot in Figure 30.

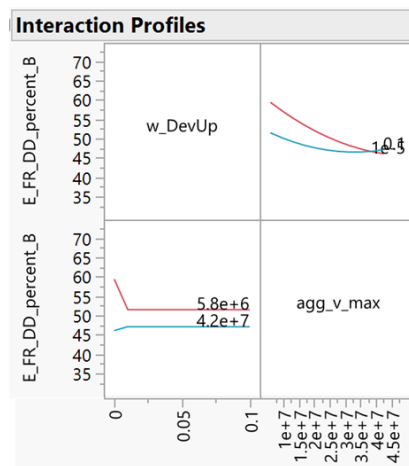


Figure 30. Interaction influence of factors on $E_FR_DD_percent_B$

The interaction plot highlights how the PID MOP for *band B* fill rate is affected when both w_DevUp and agg_v_max is at their lowest limits. The number of items that meet the fill rate is presumed to improve when giving less importance to churn by decreasing the weight of the global churn in the objective function. But, at the lowest budget limit, the number of items that deviate below fill rate increases when giving less importance to churn by decreasing the weight of the global churn to its lowest limit.

G. PID MOP FOR BAND B CHURN

The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the *Churn_percent_B* MOP are shown in Figure 31 along with the sorted parameter estimates.

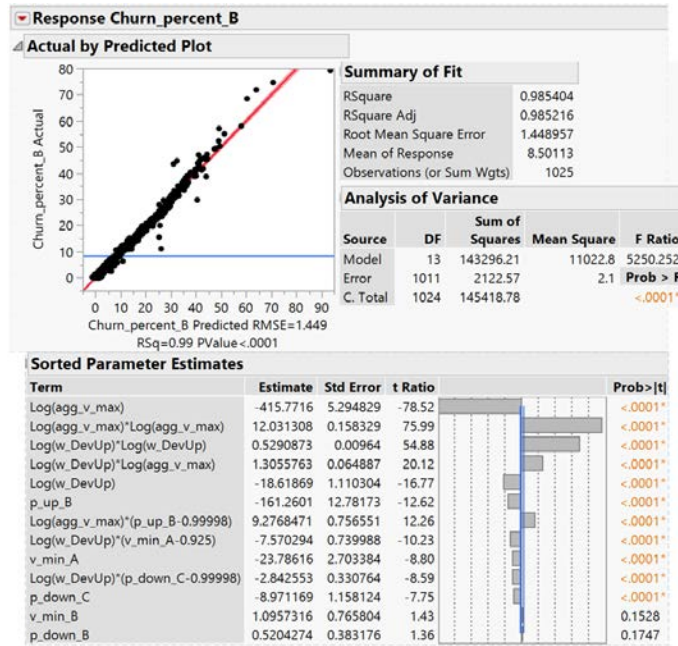


Figure 31. *Churn_percent_B* metamodel

The metamodel in Figure 31 helps us describe the sensitivity of the *band B* percent of items with deviation from zero churn (PID MOP for *band B* churn) with respect to the changes in the input value of *agg_v_max*. The quadratic form of the PID MOP for *band B* churn response surface indicates that minimum items incurring churn can be achieved at a certain budget constraint.

The PID MOP for *band B* churn is also sensitive to *w_DevUp*. As *w_DevUp* value increases from near zero to less than 0.02, a rapid decline in the number of items with churn is observed. However, for values of *w_DevUp* greater than 0.02, the decline in the number of items with churn becomes less significant. The scale factor for *band B* fill rate penalty does not have significant effect on PID MOP for *band B* churn.

The response surface of PID MOP for churn in *band B* is also sensitive to the interaction of w_DevUp with other input variables as shown in Figure 32.

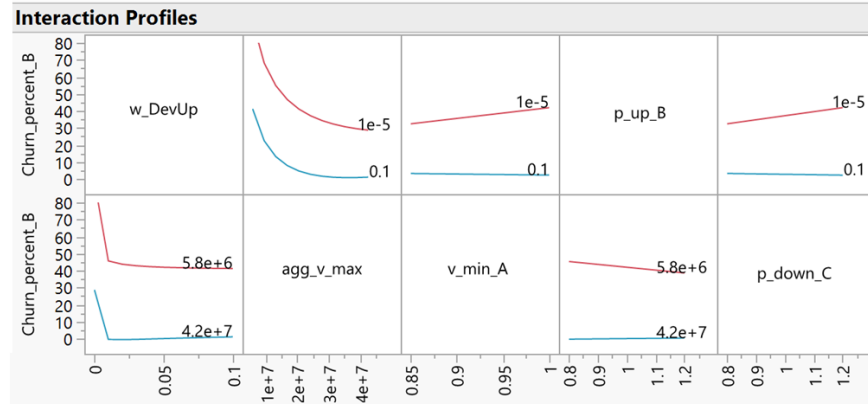


Figure 32. Interaction influence of factors on $Churn_percent_B$

The interaction plot highlights the effect of interaction between p_up_B and agg_v_max as well as the effects of interactions between v_min_A , p_down_C , and w_DevUp . The gradient of the curves in Figure 32 indicates the correlation between the *band B* number of items with churn and the input values.

H. QL MOP FOR BAND C FILL RATE

The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the $E_FR_DD_QLF_C$ MOP are shown in Figure 33 along with the sorted parameter estimates.

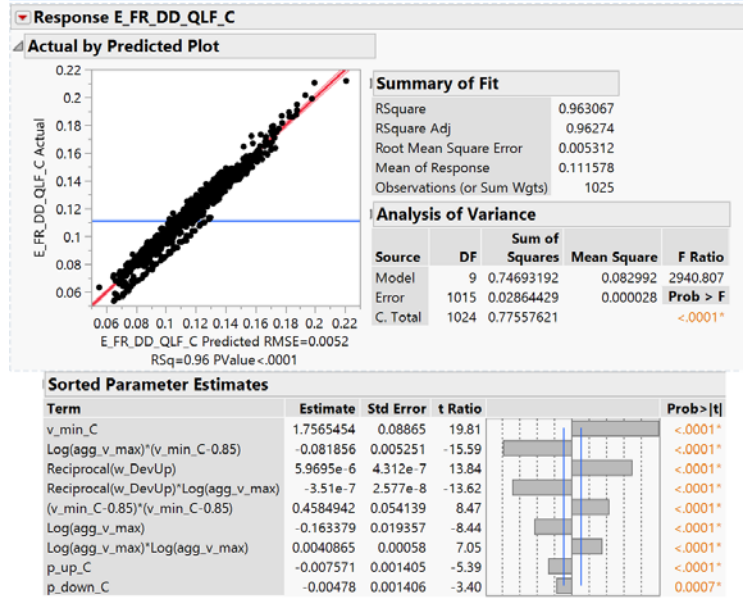


Figure 33. $E_{FR_DD_QLF_C}$ metamodel

The metamodel in Figure 33 helps us describe the sensitivity of the *band C* fill rate magnitude of deviation below the target fill rate (QL MOP for *band C* fill rate) with respect to the changes in the input values of minimum fill rate target v_{min_C} , budget agg_v_max , global churn weight w_DevUp , and the scale factors for churn and fill rate in *band C*. The order of sensitivity to each input as shown in the sorted parameter estimates indicates that fill rate in *band C* is most sensitive to the minimum target fill rate v_{min_C} and its interaction with budget constraint agg_v_max . Increasing the budget improves the fill rate of items in *band C*. The fill rate in *band C* is not very sensitive to the scale factor for the fill rate and churn penalties.

The QL MOP for the *band C* fill rate is also sensitive to the interaction between agg_v_max and w_DevUp as shown in Figure 34. When w_DevUp is near zero the effects of the budget constraint become more significant and decreasing the importance of churn decreases the fill rate.

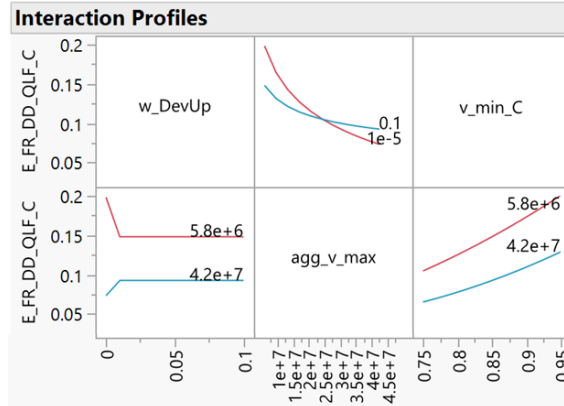


Figure 34. Interaction influence of factors on $E_{FR_DD_QLF_C}$

The metamodel of the QL MOP for *band C* fill rate highlights that the effects of the penalty scale factors in *band C* are minimal on the fill rate in *band C*.

I. QL MOP FOR BAND C CHURN

The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the $AbsChurn_DU_QLF_C$ MOP are shown in Figure 35. Our ability to establish the metamodel for churn in *band C* is diminished as observed in the actual by predicted plot and comparison of the adjusted *R-square* to other metamodels. It is possible that there are multiple PMSS levels that satisfy the objective function for churn in WIOM-ERP optimizer. Further investigation to identify the cause of this phenomenon is beyond the scope of this study.

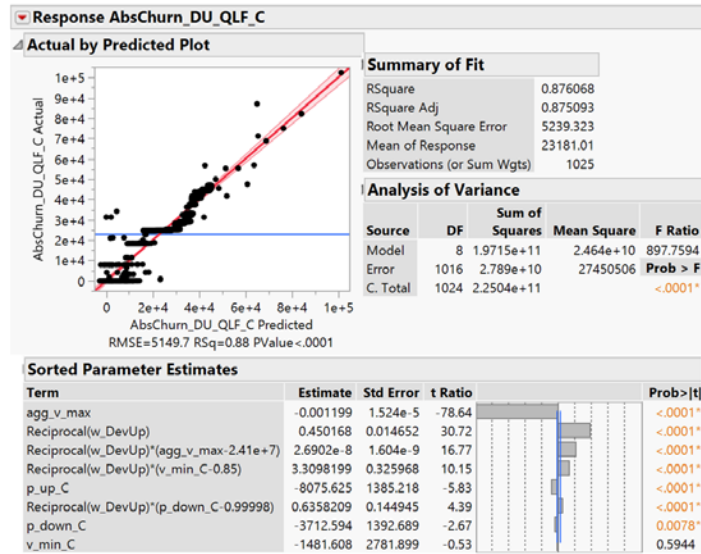


Figure 35. *AbsChurn_DU_QLF_C* metamodel

The metamodel in Figure 35 helps us describe the variation of the *band C* churn magnitude of deviation from zero (QL MOP for *band C* churn) with respect to the changes in the input values of *agg_v_max*, *w_DevUp*, *p_up_C*, *p_down_C*, and *v_min_C* in the order of sensitivity. The QL MOP for *band C* churn is very sensitive to the budget constraint *agg_v_max*. Increasing the budget improves the churn in *band C*; however, when *w_DevUp* is near zero, churn in *band C* relation to *agg_v_max* reverses. The interaction effects of these input values are shown in Figure 36.

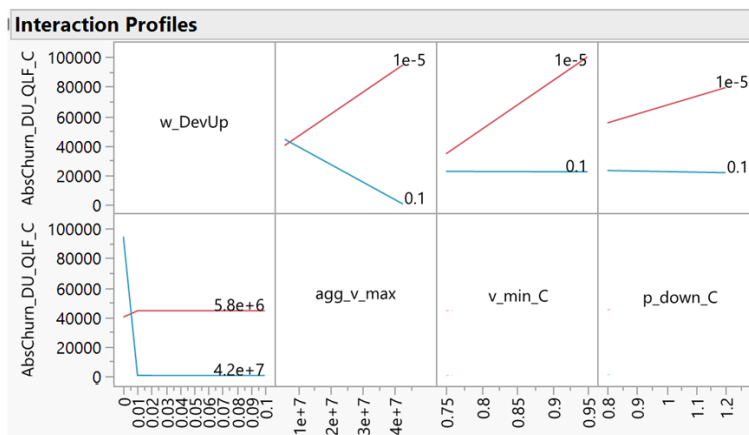


Figure 36. Interaction influence of factors on *AbsChurn_DU_QLF_C*

Churn in *band C* decreases when the churn penalty scale factor in *band C* increases. The interaction plot in Figure 36 also indicates the significant change of the response surface to v_{min_C} and p_{down_C} when w_{DevUp} is at its lowest limit.

J. PID MOP FOR BAND C FILL RATE

The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the $E_{FR_DD_percent_C}$ MOP are shown in Figure 37 along with the sorted parameter estimates.

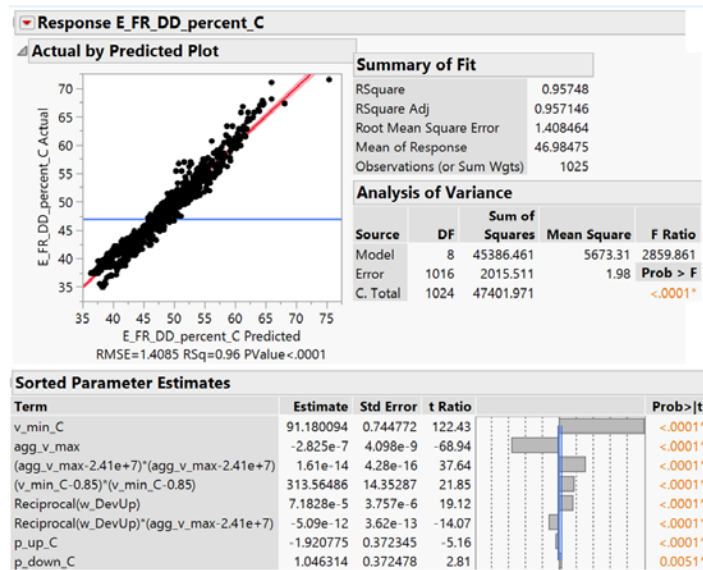


Figure 37. $E_{FR_DD_percent_C}$ metamodel

The metamodel in Figure 37 helps us describe the sensitivity of the *band C* percent of items with deviations below target fill rate (PID MOP for *band C* fill rate) with respect to the changes in the input values of v_{min_C} , agg_v_max , and w_{DevUp} . As the budget decreases, the likelihood of items deviating below the target fill rate increases in *band C*.

Changing the weight of the global churn deviation w_{DevUp} does not have a significant effect on the PID MOP for *band D* fill rate. However, when w_{DevUp} is near zero the effects of the budget constraint become more significant as shown by the interaction plot in Figure 38.

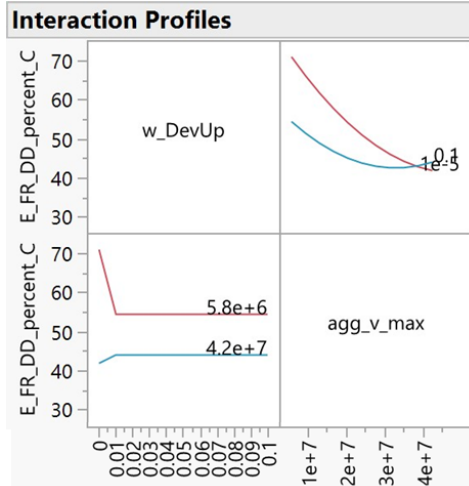


Figure 38. Interaction influence of factors on $E_FR_DD_percent_C$

The interaction plot highlights how the PID MOP for *band C* fill rate is affected when both w_DevUp and agg_v_max are at their lowest limits. The number of items that meet the fill rate is presumed to improve when giving less importance to churn by decreasing the weight of the global churn in the objective function. But, at the lowest budget limit, the number of items that deviate below fill rate increases when giving less importance to churn by decreasing the weight of the global churn to its lowest limit.

K. PID MOP FOR BAND C CHURN

The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the $Churn_percent_C$ MOP are shown in Figure 39 along with the sorted parameter estimates.

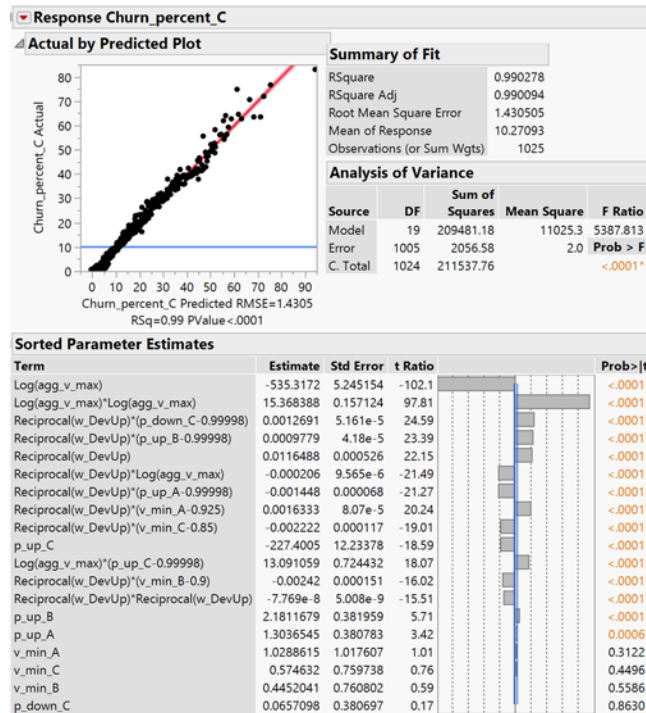


Figure 39. *Churn_percent_C* metamodel

The metamodel in Figure 39 helps us describe the sensitivity of the *band C* percent of items with deviations from zero churn (PID MOP for *band C* churn) with respect to the changes in the input value of *agg_v_max*. The quadratic form of the PID MOP for *band C* churn response surface indicates that minimal churn can be achieved at a certain budget constraint.

PID MOP for *band C* churn is also sensitive to *w_DevUp*. As *w_DevUp* value increases from near zero to less than 0.02, a rapid decline in the number of items with churn is observed. However, for values of *w_DevUp* greater than 0.02, the decline in the number of items with churn becomes less significant. The response surface of PID MOP for churn in *band C* is also sensitive to the interaction of *w_DevUp* with other input variables as shown in Figure 40.

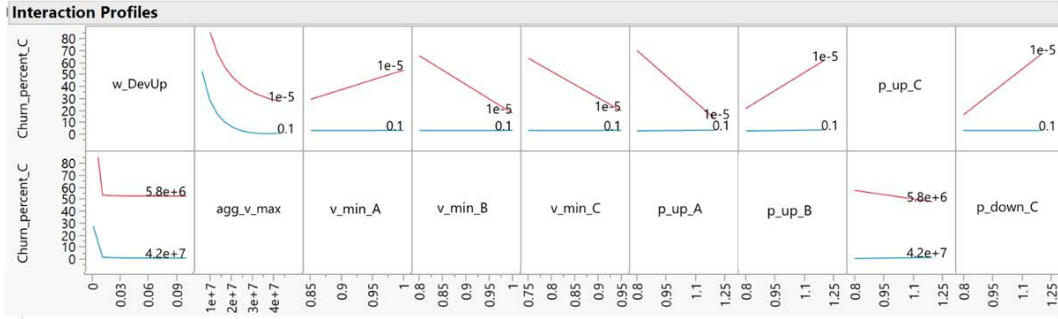


Figure 40. Interaction influence of factors on $Churn_percent_C$

The interaction plot highlights the significant effect of minimum target fill rate and churn penalty scale factors in *bands A and B* when w_DevUp values are near zero. The gradients of the curves in Figure 40 indicate the correlation between the *band C* number of items with churn and the input values.

L. QL MOP FOR BAND D FILL RATE

The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the $E_FR_DD_QLF_D$ MOP are shown in Figure 41 along with the sorted parameter estimates.

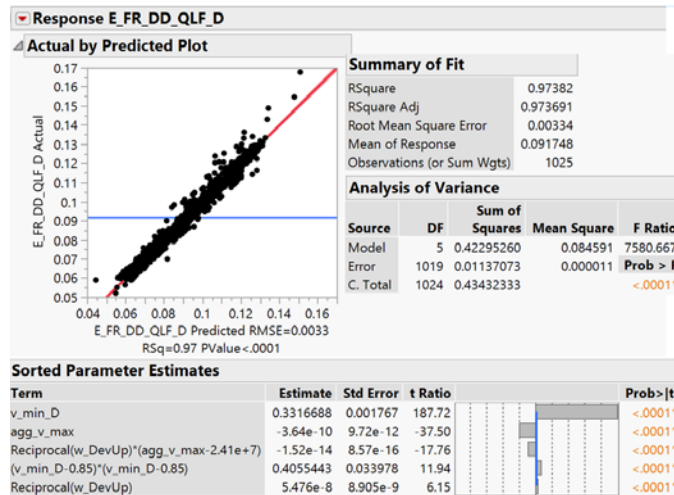


Figure 41. $E_FR_DD_QLF_D$ metamodel

The metamodel in Figure 41 helps us describe the sensitivity of the *band D* fill rate magnitude of deviation below the target fill rate (QL MOP for *band D* fill rate) with respect to the changes in the input values of the minimum fill rate target v_{min_D} , budget agg_v_max , and global churn weight w_DevUp in order of sensitivity. Increasing the budget improves the fill rate of items in *band D*.

The QL MOP for *band D* fill rate is also sensitive to the interaction between agg_v_max and w_DevUp as shown in Figure 42. When w_DevUp is near zero the effects of the budget constraint become more significant.

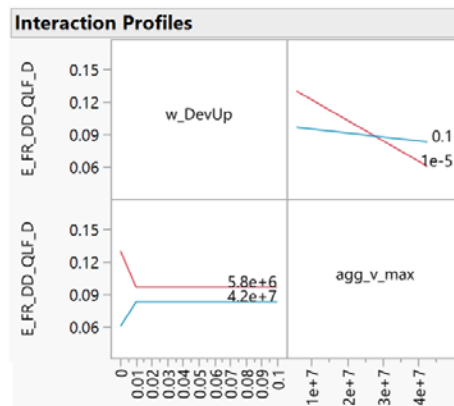


Figure 42. Interaction influence of factors on $E_FR_DD_QLF_D$

The metamodel of QL MOP for *band D* fill rate highlights that the effects of the penalty scale factors in *band D* are negligible on the overall fill rate in *band D*.

M. PID MOP FOR BAND D FILL RATE

The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the $E_FR_DD_percent_D$ MOP are shown in Figure 43 along with the sorted parameter estimates.

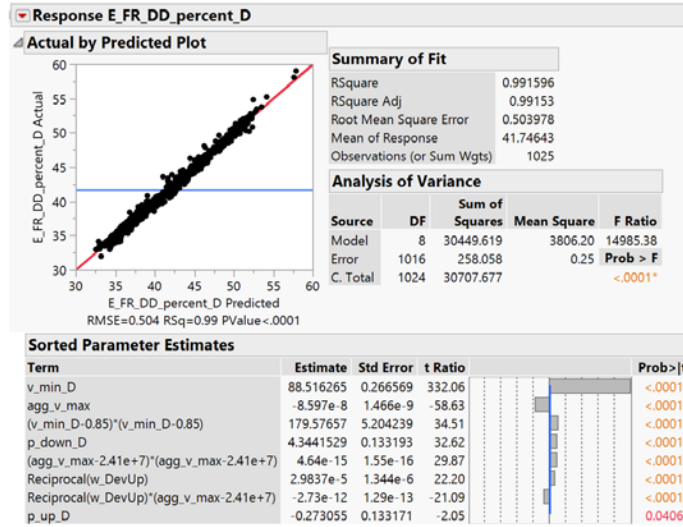


Figure 43. $E_FR_DD_percent_D$ metamodel

The metamodel in Figure 43 helps us describe the sensitivity of the *band D* percent of items with deviation below target fill rate (PID MOP for *band B* fill rate) with respect to the changes in the input values of v_min_D , agg_v_max , and w_DevUp . The PID MOP for *band D* fill rate is mostly sensitive to *band D* minimum target fill rate. The PID MOP for *band D* fill rate is slightly sensitive to the Budget constraint agg_v_max . Decreasing the budget causes a small increase in the likelihood of items deviating below the target fill rate in *band D*.

Changing the weight of the global churn deviation w_DevUp does not have a significant effect on the PID MOP for *band D* fill rate. However, when w_DevUp is near zero the effects of the budget constraint become more significant as shown by the interaction plot in Figure 44.

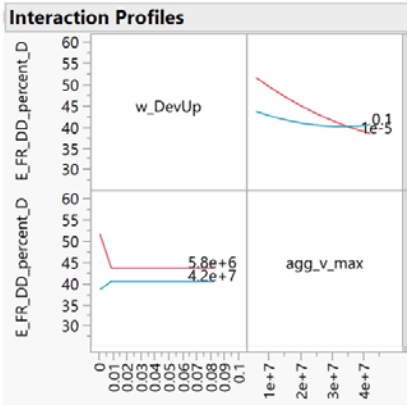


Figure 44. Interaction influence of factors on $E_FR_DD_percent_D$

The interaction plot highlights how PID MOP for *band D* fill rate is affected when both w_DevUp and agg_v_max are at their lowest limits. The number of items that meet the fill rate is presumed to improve when giving less importance to churn by decreasing the weight of the global churn in the objective function. But, at the lowest budget limit, the number of items that deviate below the fill rate increases when giving less importance to churn by decreasing the weight of the global churn to its lowest limit.

N. PID MOP FOR BAND D CHURN

The diagnostic plots and summary of fit diagnostics for the metamodel that we use to describe the factor effects on the $Churn_percent_D$ MOP are shown in Figure 45 along with the sorted parameter estimates.



Figure 45. *Churn_percent_D* metamodel

The metamodel in Figure 45 helps us describe the sensitivity of the *band D* percent of items with deviation from zero churn (PID MOP for *band D* churn) with respect to the changes in the input value of *agg_v_max*, *w_DevUp*, *p_up_D*, and the interaction of *w_DevUp* with target fill rate and penalty scale factors of *bands C* and *B*.

PID MOP for *band D* churn is sensitive to *w_DevUp*. As *w_DevUp* value increases from near zero to less than 0.02, a rapid decline in the number of items with churn is observed. However, for values of *w_DevUp* greater than 0.02, the decline in the number of items with churn becomes less significant. The scale factor for *band D* fill rate penalty has a negligible effect on PID MOP for *band D* churn.

The response surface of PID MOP for churn in *band D* is also sensitive to the interaction of *w_DevUp* with other input variables as shown in Figure 46.

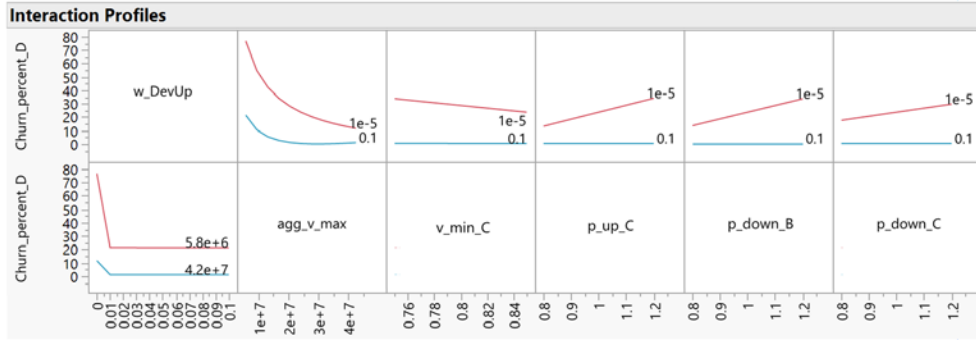


Figure 46. Interaction influence of factors on $Churn_percent_D$

The interaction plot highlights the significant interaction effects of w_DevUp with v_min_C , p_up_C , p_down_C , and p_down_B when w_DevUp is near zero. The gradient of the curves in Figure 46 indicates the correlation between the *band D* number of items with churn and the input values.

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