Options-based Planning for Mass-Customization: A Simulation-Optimization Model

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Increasingly, customers expect products highly customized with reduced lead-times. Additionally, intense geopolitical, economic and regulatory uncertainties render long lead-times increasingly risky for both equipment suppliers and customers alike. This article presents a mass customization model called options-based planning (OBP) which is better adapted to complex market realities than legacy production models. A discrete event simulation examines the performance of the new model compared to legacy production strategies. Under conditions of high market turbulence (i.e. trade wars, pandemics, etc.), the new model allows shorter customer lead-time while maintaining the high level of customization expected of highly valued capital equipment.

Keywords: capital equipment, mass-customization, production planning, discrete-event simulation, mixed-integer programming, real options, build-to-forecast

INTRODUCTION

Capital equipment (e.g., industrial robots, MRI machines, and CNC machines) have comparatively long build times, high design customization and are expensive (Salvador and Forza, 2004; Raturi, Meredith & McCutcheon, 1990; Tuovila, 2019). Market disruptions (e.g. natural disasters, pandemics, financial crisis) can affect the entire rationale for a capital equipment acquisition. A financial crisis can create even more uncertainty than natural disasters with a known geographic epicenter because it creates widespread uncertainty about supply and demand (Sheffi, 2015). Additionally, competitive pressure for shorter product life requires firms to pursue both customization *and* responsiveness (i.e. shorter delivery time) from capital equipment suppliers: the customization-responsiveness squeeze (C-R) (Raturi et al., 1990).

This research introduces a new solution to the classic C-R squeeze called options-based planning (OBP). The new model leverages the comparative stability of the demand schedule (due to customers' long capital expense planning timelines) while dispensing with the need to forecast volatile product design requirements. It does this by utilizing real-options to create flexible design features that can be added when an actual customer order arrives – similar to traditional MTO production. A real option is a right, but not the obligation, to a course of action. For example, one could purchase a new car and have a fog lamp added at the dealer; this design parameter would not have had to be committed at the start of the build cycle. Additionally, the customer need not purchase this feature (option not called).

Flexible design parameters (real options) not only include end-stage accessorizing but can also encompass customer supplied/designed hardware with significant intellectual property content. This can be the result of a highly collaborative alliance (between supplier/buyer) where each firm invests in the development of new product technologies which also create partnership synergies with "…an anticipation of achieving strategic and/or profit objectives" (Dahlquist, 2015). Alternatively, a flexible design feature can be the result of an emerging market supplier who provides a specific deliverable (e.g. component) committed to a leading firm to an established product architecture (Chen & Jaw, 2019). This, in turn, can often be the result, of a major multinational firm seeking to localize a portion of its production through foreign direct investment in a market with a favorable governance environment (e.g. absence of corruption) (Banerjee,2019).

Specifically, this paper seeks to examine two research questions:

RQ1: *How does product customization, delivery responsiveness, and design commitment influence market fulfillment?*

RQ2: *Under what conditions does the OBP model outperform legacy mass-customization models?*

This paper is organized as follows. First, we briefly review the literature on mass-customization to introduce the "classic" Build-to-Forecast (BTF) model. Next, we introduce the new options-based planning model (OBP) and compare it to the BTF model which will be used as a benchmark to compare to the new model. We then present a discrete-event simulation optimization model which mimics elements of the production planning logic of a major multinational manufacturer of capital equipment to solve an assignment problem (product-sales order match). A simulation is a powerful technique to investigate scenario-specific conditions in complex environments and shed light on possibly unexpected outcomes (Choi & Wu, 2018). The results are then used to compare how the new and legacy model performs over the entire space of customization-responsiveness. From this, practical lessons are articulated, and the managerial implications are discussed. Finally, we discuss the limitations of the study and propose suggestions for future research.

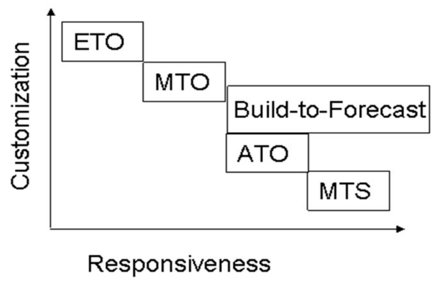
LITERATURE REVIEW

Conventional Production Strategies

Prior to introducing the BTF and OBP production models, a brief description of conventional production strategies will broadly set the context for the mass-customization models. Figure 1 shows the traditional production models on the customization vs. responsiveness axis.

The most customized, but least responsive (longer lead time) production strategy, is engineer-to-order (ETO). No design or procurement activities occur until receipt of an actual sales order. The product is engineered specifically to that order from first principles (e.g. building or hydroelectric dam). Somewhat less customized but more responsive is make-to-order (MTO) production, where there is an existing design or template that allows for a high (but not total) level of customization using design variants but the build cycle does not commence until a sales order arrives. Assemble to order (ATO) has subassembly components in stock and the final product is assembled to match the order. An example of this model is used by Dell computers. Make to stock (MTS) is the most responsive production strategy but allows for essentially no customization. The final product is of standardized design and demand is serviced from a finished goods inventory.

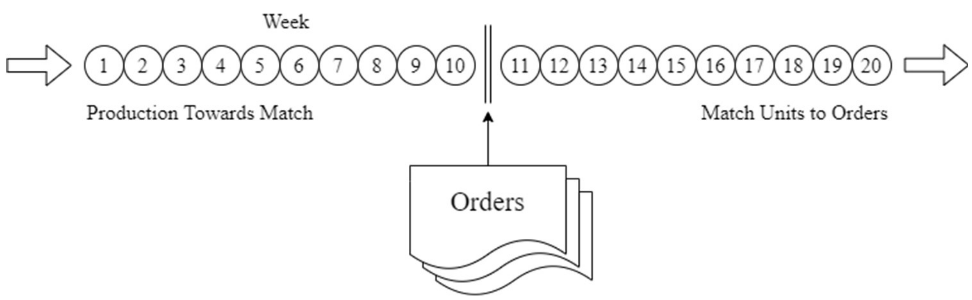
FIGURE 1
PRODUCTION STRATEGIES



Customization-Responsiveness Squeeze and Build-to-Forecast Model

The Build-to-Forecast (BTF) model has its origin in the machine tool industry in the 1990s and was developed as an original solution to the C-R squeeze (Raturi et al.,1990; Raturi et al., 1994). The BTF model was further characterized in McCutcheon et al. (1994) and Meredith & Akinc (2007). Figure 2 is a simplified representation of the BTF model highlighting how sales orders are matched against the work-in-progress inventory throughout the build cycle.

FIGURE 2
THE PRODUCTION AND ORDER-MATCHING PROCESS IN THE BTF SITUATION



(Adapted from Meredith & Akinc, 2007)

A major limitation of the original BTF model is that it assumes the customer design requirements of a future sales order can be accurately forecasted. This is problematic since design requirements can be very volatile. For example, while telecommunications equipment is highly configurable, McGuinness and Wright (1998) found in a case study that AT&T incurred excessive configuration errors due to the fast-changing product design requirements between the time of sales order receipt and product installation.

Design Flexibility and Bill of Materials

Firms preserve and organize information about the product structure in a form of *bill of materials*, or BOM. The BOM is more than an itemized listing of parts, documents, and text, but rather is a key piece of business data that drives manufacturing, purchasing and accounting (Mather, 1982). Rusk (1990) discusses how a BOM serves the needs of the whole organization (e.g. design procurement, cost accounting, etc.). The structure of the BOM strongly influences a product's build sequence. For example, a multi-level BOM – as used in the original BTF model - would be built up from components, then into sub-assemblies then into a final product. A flat BOM – as in a lean design using a modularized design – would have fewer build-sequence dependences– the final assembly is assembled from components relatively independent of each other in build order.

FIGURE 3
BOM STRUCTURE AND SHOP FLOOR ORGANIZATION

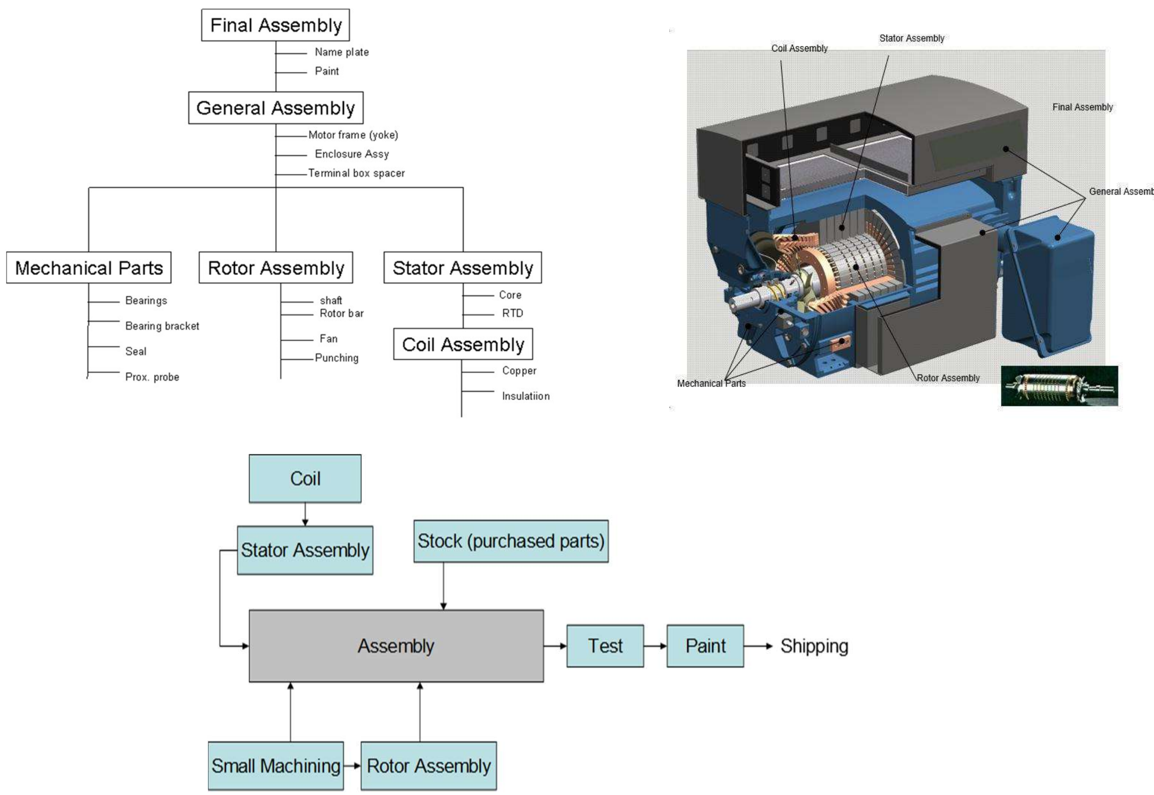


Figure 3 shows an example of an ANEMA (above 500HP) AC induction motor schematically and how the BOM structure influences the build sequence. The structure of the BOM and the layout of the production floor closely align. An important feature of this example is the BOM is relatively flat (as in a lean production) and is built in place (Garwood, 2001) rather than moving down an assembly line.

A lean BOM structure is more realistic in the customization and responsiveness squeeze for two reasons. First, the effects of design forecast errors on a lean (i.e. flat) BOM are less pronounced than for a multi-level BOM structure (a major limitation of the BTF model) because modules can simply be swapped out with minimal rework required for other components. The other reason is that many products – like the industrial motor used as an example below – are assembled in place using project-based production. That is, the build area for that product is occupied from build initiation to completion.

Real-Options Theory

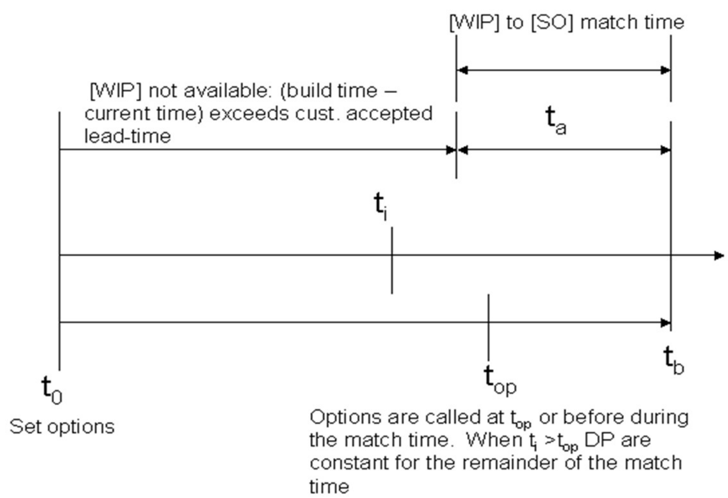
In general, there are two types of options used to hedge against potential risks and uncertainties: financial options and real-options. Myers (1977) coined the term "real options" to extend the idea of financial options to the realm of strategic decision making, specifically, the right, but not obligation, to purchase an asset. Like financial options, real options have a *call time;* a time after which that right to exercise the option expires, and the selection is fixed. In the context of strategic investment choices, Trigeorgis & Reuer (2017) introduce a taxonomy of real options by type that enable an investment to: defer, grow, alter scale, switch, or exit. For our research, we consider a real option as the ability to *defer* a design decision. A design decision is an investment of human and financial capital that results in the creation of a product feature which is a unit of intellectual property.

TOWARD AN OPTIONS-BASED PLANNING MODEL

Options-Based Planning Model Description

In this section, we introduce an Options-based planning model to improve existing C-R squeeze attempts (e.g., BTF). In the BTF model, a forecast specifies both the expected timing and the functional requirements of future sales orders. In contrast, the OBP plan does not use a forecast to completely specify the final product configuration. Rather, the forecast only controls the product release schedule and design features that are fixed (DP), and the forecast does not include those design features that are not mandatory – i.e. they are not intrinsic to its design or legally mandated features. Below, we explain the working logic of the OBP model as a function of time and figure 4 shows the events of the OBP model.

FIGURE 4
TIMELINE OF THE OPTIONS BASED PLANNING MODEL



The OBP model assumes products release in waves, or cohorts. A staggered release schedule would not affect how OBP is modeled. The forecast specifies only the expected arrival times of the sales order, not specifically what non-standard features the orders will require. At build initiation (t_o in figure 4) all products in the wave commence the build. All work-in-process (WIP) in the release wave have the same number of fixed DP (but each WIP can have different standard feature packages) and the options all expire at the same time (t_{op}). The common option call time makes the simulation logic more parsimonious and does not detract from the realism of the model since all WIP start and end the build-cycle at the same time. in figure 4) all products in the wave commence the build. All WIP in the release wave have the same number of fixed DP (but each WIP can have different standard feature packages) and the options all expire at the same time (t_{op}).

Once the build cycle is underway (t_i) and until the match window, the construction of the product commences. Sales orders arriving before the match time are ignored since there is too much build time remaining for how long the customer is willing to accept (t_a). In this case, it is the same as the order never arriving at all (i.e. it is not sellable demand). The simulation will only attempt to match sales orders to products whose remaining build-time is less than, or equal, to t_a. As sales orders arrive, the planner will attempt to match a product to that order by calling options as needed to generate matches between the sales order and product. Products that cannot be matched to order are "orphans" and cannot be held in inventory.

They are too customized and occupy a significant portion of shop floor space. They are disposed of either through teardown or sold in secondary markets at a steep discount.

Real-Options-enabled Decoupling Mechanisms

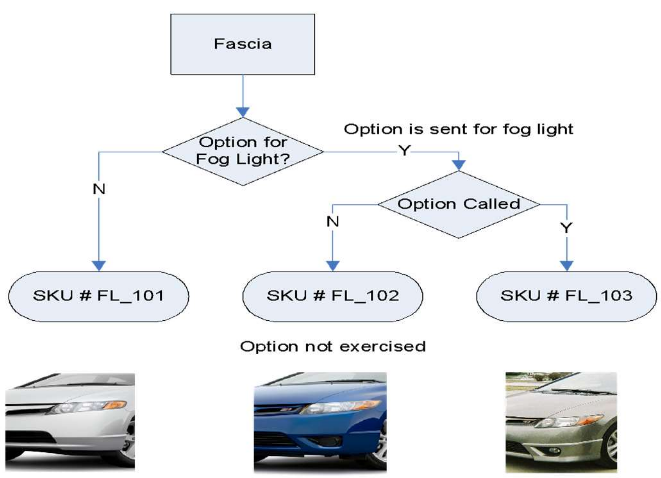
Options-Based Planning (OBP) model incorporates the real options concept during the decoupling process. Thus, key features of OBP model include: (1) *Real options are the right, but not obligation*, to take a future course of action in non-financial transactions (Trigeorgis, 1996). In a configurable design, a real option enables a flexible design feature that allows a future component selection. This is a characteristic of capital equipment where customers expect more customizability than option bundles, (2) It also reflects the *sometimes-modular nature of capital equipment design features (i.e. "bolt on")* where customers may design, or actually supply hardware, to be added to the supplied product and use customer-supplied hardware. (3) Options expire at their call time. While the option call time may coincide with the end of the build cycle, it can also occur prior to build completion if there is appreciable component acquisition lead-time or installation time.

The next section presents a consumer product example to illustrate how real options enable flexible design features in the OBP model.

Real Options: An Example

A fog light is often offered as a dealer-installed accessory that can be added shortly before a customer arrives to get the new car they purchased. The front fascia where the lamp would mount, however, is not dealer-installed but must be installed earlier in the build cycle at the factory. To accept a fog light, a fascia must be supplied which could allow the lamp to be installed. Thus, the fascia embodies all aspects of a real option. There are two different fascia designs: one that enables the installation of the light (real option), the other does not (no option). In the example here, a fascia is supplied by the factory with a cut-out (an option that allows the lamp to be installed). Should the customer not select the light (option unexercised), a blank is inserted in the cutout. Otherwise, when the option is called, a light is installed since the fascia can accept this feature.

FIGURE 5
REAL OPTIONS, AN EXAMPLE



Had a cheaper and simpler fascia been supplied (options increase design complexity), then the fog light option would not have been available to the customer had they requested it. Thus, the customer would have had to accept a car without the fog light as they originally requested, a 'compromise match', or they would not have selected the product.

In this example, the seat belts are not an option; they are a fixed design parameter (DP) required by law and do not need to be forecasted nor is there a need for flexible DP. Air-conditioning is not legally required but is so commonly specified by the customer that neither a design forecast nor design flexibility provides many benefits. However, design parameters not mandatory, standard, or universally expected (i.e. discretionary to the customer) may be flexible and offered as an option.

Thus, the options-based planning (OBP) model is an extension of the earlier BTF model and retains the original BTF logic for selecting the product features that are fixed and discretionary while allowing MTO customizable on purely discretionary design parameters (i.e. product upgrades from a base functional model).

The OBP model reduces product configuration errors (mismatch to customer requirements) because the flexible DP (with options) does not need to be forecast. In fact, for a fully customizable product (all features are selectable) there would be no product design forecast at all. An example can be found in a case study of the Build-A-Bear Workshop who is able to offer the customer full customization without the need to carry a finished goods inventory of toys (Zabeen & Chowdhury, 2017).

This research investigates the effects of customization, responsiveness, and design commitment on order fulfillment performance in an OBP context. It is based on a discrete event simulation which models the assignment of products to orders as those orders emerge later in the product build cycle. The simulation logic is specific to the OBP model (lean BOM structure, wave release strategy) which is very distinct from the original BTF model logic.

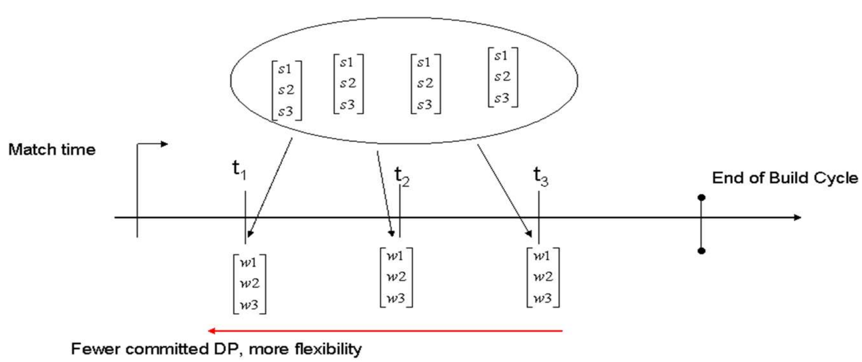
RESEARCH METHODOLOGY - A SIMULATION OPTIMIZATION MODEL

An Optimization-Simulation Approach

To examine the potential baseline of the OBP model, we examine the working dynamics of OBP models in the entire space of customization-responsiveness using a *discrete event simulation optimization model*. A discrete event simulation framework discretizes time into "snapshots of time (e.g., into a day)". This allows the work-in-progress and sales order matching to be solved as a binary integer programming problem successively in time. The model is updated at the end of each time-step.

We model both the sales order and work-in-process as vectors with binary elements. The sales order vector consists of customer functional requirements represented as a binary element (required/not required). Raturi et al. (1996) introduce a design parameter as a product design feature that corresponds to a functional requirement in a sales order. To use a binary element (present/not present) vector representation of sales orders and products, let functional requirements be defined as an element in a sales order vector and a design parameter an element in the WIP vector. The figure below visualizes the matching process.

FIGURE 6
ORIGINAL BUILD TO FORECAST MODEL



Assuming a product has a total of Nconfigurable parts, let the sales order vector be s and the WIP vector be w, then the level of match between a pair of sales orders and a WIP can be expressed as a simple matching coefficient below:

$$SMC = 1 - \frac{1}{N}\sum_{i=1}^{N}(s_i - w_i)^2 \tag{1}$$

In the best-case scenario, there will be a 100% element to element match between the sales order (SO) and WIP, but the match between the sales order and product need not be 1:1 as the customer may be incentivized to accept a product that is not exactly what they had wanted, yet still acceptable. Were the functional requirement and design parameters not binary, then an alternative mapping logic would need to be employed (Fung et al., 1998).

In this simulation, the binary integer programming takes the form of an assignment problem. It is an optimization technique often used to identify resource allocation plans that maximize or minimize the outcome (e.g. cost minimization, skill-match maximization, etc.). An excellent example can be found in Lapin & Whisler (2002) who illustrate the technique by solving a managerial problem of allocating skilled machinists to the requirements of a specific job. In this simulation, each day, arriving sales order(s) attempt to find the match(es) with the available WIPs that can maximize the total coefficient. We formalize the maximization problem below.

Let:

- i be the number of functional requirements and $i \in \{1,2,3, \dots N\}$
- k be the number of standing sales orders to fulfill each time and $k \in \{1,2,3, \dots K\}$
- j be the number of remaining work-in-progress and $j \in \{1,2,3, \dots J\}$
- s be the sales order;
- w be the work-in-progress;
- y be the decision variable that indicates the match $y_{jk} \in \{Yes = 1, No = 0\}$ between a sales order s_k and a WIP w_j;
- T be the matching threshold level;

Identify all y_{kj} that maximize the sum of the simple matching coefficient for all the k orders:

$$\sum_{k=1}^{K}\sum_{j=1}^{J} SMC_{kj} = \sum_{k=1}^{K}\sum_{j=1}^{J} y_{kj} \cdot \left[1 - \frac{1}{N}\sum_{i=1}^{N}\left(s_{ki} - w_{ji}\right)^2\right] \tag{2}$$

subject to:

- $\sum_{k=1}^{K}\sum_{j=1}^{J} y_{kj} \leq \min\,(J, K)$

$\sum_{j=1}^{J} y_{kj} \leq 1$, for each $k \in \{1, 2, \dots, K\}$
$\sum_{k=1}^{K} y_{kj} \leq 1$, for each $j \in \{1, 2, \dots, J\}$

- $y \in \{0,1\}$
- $SMC_{kj} \geq T$, if $y_{kj} = 1$

In each time-step (in our case, a day), once the obtained matching coefficient(s) are higher than a predefined threshold level, then the match(es) are made. Subsequently, the boundary conditions (e.g., number of remaining WIP, etc.) are updated then the time is "marched" forward. This process is repeated until the entire building cycle is finished.

The complete simulation logic is shown below (figure 7) in the form of a flowchart.

Numerical Setting

Below, we explain the numerical setting of the simulation. Three variables control the overall performance of the matching: the level of design commitment, the level of responsiveness requirement, and the level of customization in design. For each variable, we divided the value space into four levels. This partition treatment has several merits. While reducing the computational burden of the model, at the same time, it will allow us to observe whether consistent patterns can be observed as the values of the variables increase from a lower value to a higher one.

Below, we present them in a standardized form in table 1. This form of presentation intuitively shows the extent of the influence of each variable. In the actual simulation, we used the build cycle of 50 days with 10 total design parameters setting. Thus, xOpt=.3, $Ta = .5$, and $Flex = .8$ will translate into a matching environment where the options will expire on the 15th day, the customers are willing to wait a maximum of 25 days, and 8 parts are configurable. There will be 10 sales orders ($K = 10$) arriving randomly to find a match with 10 available WIPs ($J = 10$) that are launched as the same batch. The inter-arrival time follows a uniform distribution. The sales order functional requirement binaries are also random. A match attempt is considered successful when the simple matching coefficient (SMC) is higher than the predefined threshold of 0.75. The final matching performance is calculated by the proportion of matches (out of 10 WIPs).

FIGURE 7
OPTIONS-BASED PLANNING: THE SIMULATION LOGIC

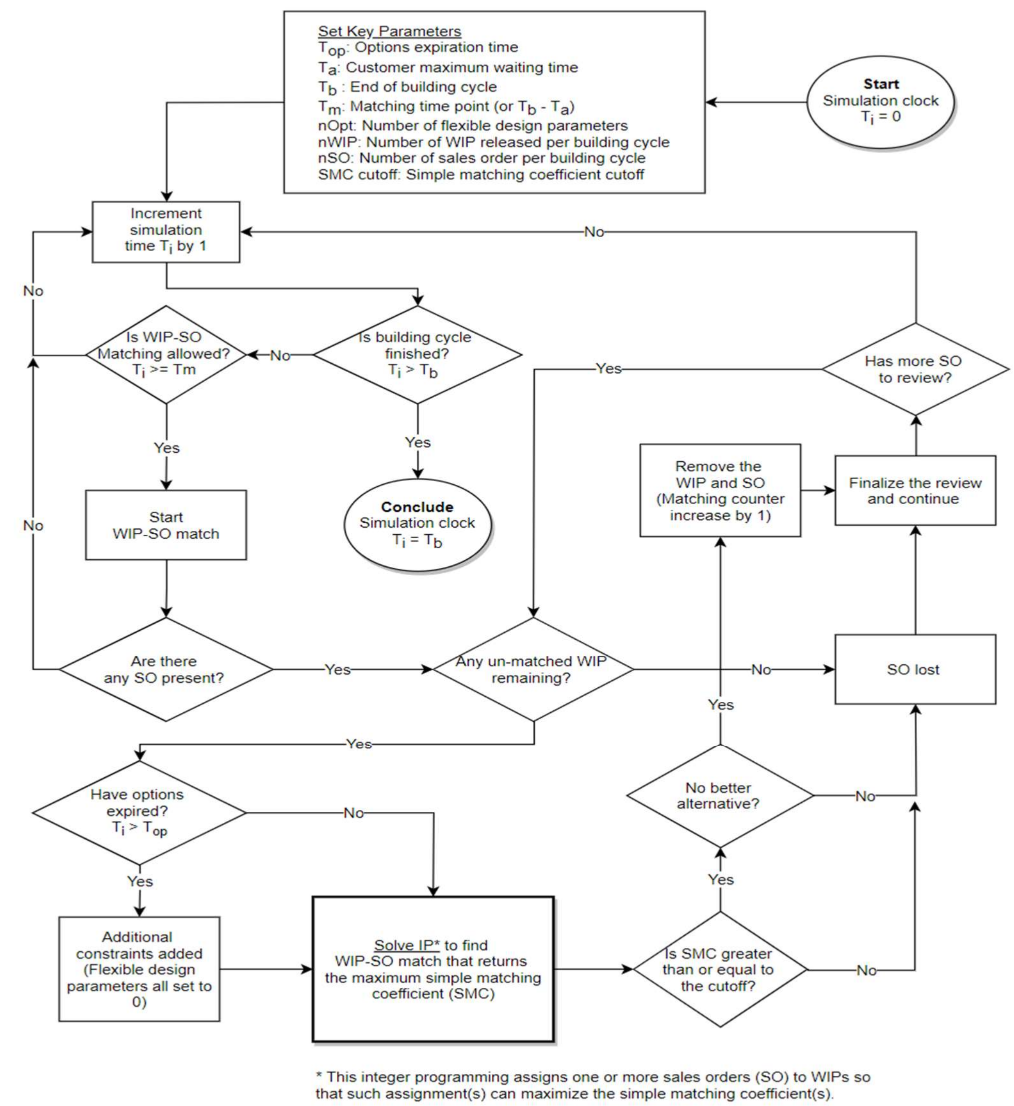


TABLE 1
VARIABLE DEFINITION AND VALUES

Dimension	Description	Variable Levels		
		Value	Study 1	Study 2
Design Commitment *Variable name: xOpt*	It is the timing at which the options will expire. A very small value means the options will be expired in very early stage of the building cycle.	0.30	Early	BTF
		0.50		Early
		0.80	Late	Late
		1.00		Very Late
Responsiveness *Variable Name: Ta*	It is the customer's expectation at which the manufacturer has to respond. A very low value means a very demanding lead time.	0.10	High	High
		0.40		
		0.75	Low	Low
		1.00		
Customization *Variable Name: Flex*	It is the extent to which WIPs are customizable. Lower value means low in customizability.	0.00	Low	Low
		0.50		
		0.80	High	High
		1.00		

While the original simulation is designed as a 4x4x4 factorial design, in the data analysis phase, we combine the levels in a different way to better serve the purpose of the study. Study 1 has a 2x2x2 factorial design while study 2 has a 4x2x2 factorial design. In study 1 we review the working dynamics of the OBP model and in study 2 we plan to compare the matching performance of the BTF model with the different levels of the OBP model. Grouping the data during the analysis phase offers an important advantage in addition to the brevity of the reporting. Below, we delineate the logic.

Analytical Advantage of Group Partitioning

The simulation variables span the entire production planning space of customization, responsiveness and early/late design commitment and model conditions at the extreme ranging from make-to-order (high customization/low responsiveness/late design commitment) to make-to-stock (low customization/high responsiveness/early design commitment). While the simulation logic (Figure 7) was developed specifically to model the OBP model, there are regions in the simulation space that closely approximate the BTF condition. Specifically, the original BTF model allows for pre-forecasted design features to be re-worked which is, in effect, a short-duration – albeit, expensive – option. Therefore, partitioning the OBP simulation data enables the comparisons between the original BTF and OBP models. Specifically, when the simulation variable xOpt=.3, the "options" have a very short call time. In the original BTF model, this would correspond to a one-time rework to compensate for the design forecast error.

The real options-enabled flexible design parameters also determine when the design must be committed to, or the order decoupling point. The decoupling point is normally understood as the level in the BOM (the products level of completeness) that the inventory is held (e.g. sub-assembly for ATO or finished goods for MTS). However, in the mass-customization context – both BTF and OBP – it also represents when the product design is fixed. For example, in a make-to-stock model, the product design is committed early (at product build initiation) whereas, for make-to-order, the design commitment occurs late – i.e. only after an order arrives. While MTS and MTO are examples of pure form production models, there can also be hybrid models that exhibit characteristics of more than one model. In the context of the C-R/design commitment space where the OBP and BTF are defined, table 2 maps out both pure-form and hybrid production.

TABLE 2
PRODUCTION MODELS IN THE C-R/DESIGN COMMITMENT SPACE

	Design Commitment			
	Early		Late	
Customization / Responsiveness	High	Low	High	Low
High	C-R Squeeze	Make-to-Stock	C-R Squeeze	Make-to-Stock Like
Low	Make-to-Order Like	Long LT – Std.	Make-to-Order	Long LT – Std.

The original C-R squeeze is the condition that motivates both the OBP and BTF models and is where both customization and responsiveness requirements are high. This applies whether the design commitment must occur early, as in BTF, or late as possible in OBP. The traditional MTS model has high responsiveness and early design commitment (at product build initiation). At the other extreme is MTO where customization is high but responsiveness is low. However, the design commitment is late because the design decision does not need a forecast, it is simply what the actual customer order specifies. There are, however, interesting hybrid conditions that design flexibility gives rise to and form the basis of the propositions that follow.

MTS-like is what Silver & Moon (2001) refers to as convertible units. These types of products may be sold "as-is" from stock or maybe customized on-demand on a limited basis. To use the previous fog lamp example, the car may be sold from stock as is or a fog lamp installed at the dealer almost on demand. MTO-like conditions can arise in the OBP model where the options have a short call time but the customer requested responsiveness is low. Thus, while some design features may need to be made early, the overall model is similar to classic MTO.

Novel for the options-based planning environment is the case that we label long lead-time standard (LLT-Std). In managerial practice, this would simply be MTO production with no allowable customization. This can occur when a product is highly engineered and standard for a market segment but consists of long to procure components and the finished product is physically large and would represent a massive amount of locked-up capital if held in stock by the manufacturer. An example of this is the ANEMA motor example previously featured. Often, a customer would simply specify speed and power they wanted and that it be "API-compliant" – American Petroleum Institute. The API requirements specify the required design attributes for the entire petroleum industry and require no further customer specifications.

TABLE 3
FREQUENCY ANALYSIS OF MATCH

Proportion of Match	Freq.	Percent	Cum.
0%	27	4.29	4.29
10%	39	6.19	10.48
20%	51	8.10	18.57
30%	76	12.06	30.63
40%	87	13.81	44.44
50%	72	11.43	55.87
60%	80	12.70	68.57
70%	90	14.29	82.86
80%	65	10.32	93.17
90%	42	6.67	99.84
100%	1	0.16	100.00
Total	630	100.00	

RESEARCH RESULTS

We ran 10 simulation runs for each of 64 original treatment groups. In this case, we would expect a total of 640 observations. However, 10 observations were removed from the no-flexibility scenarios (Flex = 0) since they represented duplicated conditions which were not conceptually distinct. Specifically, for the no flexibility scenarios (no real option-enabled design features), when the option call time $t_{op} = 1.0$, it is conceptually equivalent to when $xOpt = 0.3$ (or any arbitrary value of $xOpt$) since there are no options to call.

We review the descriptive statistics of the match and fit the data into linear regression models for statistical analysis. Below, we first report the results of study 1 and then study 2.

Study 1 Results (2x2x2)

The simulation results span the eight conditions described above (table 2) and form the basis for the subsequent discussions. In study 1, we have ending product match proportions as shown in Table 4. The cells correspond to the C-R/design space previously shown (table 2). For example, for the C-R squeeze and early design commitment, the OBP model produces a mean match proportion of .349.

TABLE 4
SIMULATION RESULTS: END PRODUCT/ORDER MATCH PROPORTION

	Design Commitment				
	Early		Late		
Customization	High	Low	High	Low	
Responsiveness	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)
High	0.349 (.201)	0.260 (.162)	0.654 (.186)	0.505 (.218)	0.446 (.247)
Low	0.419 (.190)	0.300 (.153)	0.735 (.143)	0.712 (.127)	0.523 (.243)
M(SD)	0.391 (.197)	0.284 (.158)	0.699 (.169)	0.629 (.197)	0.491 (.248)

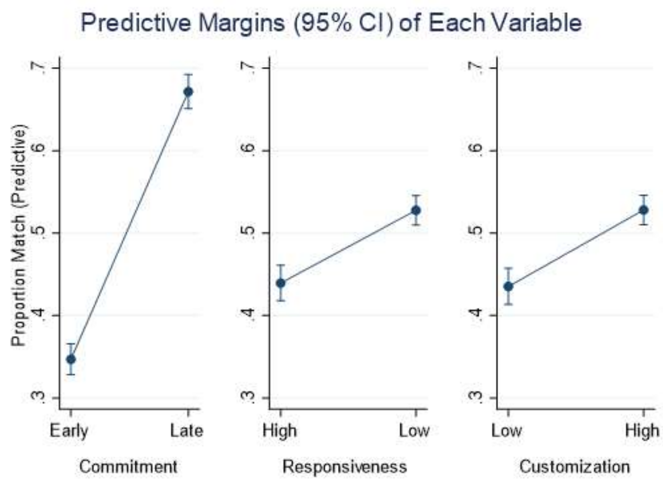
Table 5 reports the results from the regression analysis. The result shows that the three factors are significant and their direct effects explain nearly 50% of variations among the overall matches. All factors have fairly small standard errors and the variance inflation factors are lower than the threshold of 3. All variables are 2-level categorical variables; therefore, the size of the coefficient is the difference with the baseline variable level.

TABLE 5
REGRESSION RESULTS (2X2X2)

	DV: Proportion of Match	VIF
Commitment Late	0.325***	1.01
	(0.0142)	
Responsiveness Low	0.0882***	1.00
	(0.0143)	
Customization High	0.0928***	1.01
	(0.0144)	
Constant	0.239***	
	(0.0152)	
Observations	630	
R^2	0.498	

The commitment variable has the biggest coefficient size with the late commitment being 0.325 larger than the early commitment case. The differences between the two levels of responsiveness and the customization are smaller at nearly 0.1. We also reviewed the fitted results for overall matches and plotted the results below in figure 8. While holding all other factors constant, the early commitment case has overall matches of 0.35 while the number for the late commitment case is 0.67.

FIGURE 8
PREDICTIVE MARGINS OF EACH VARIABLE



Study 2 Results (4x2x2)

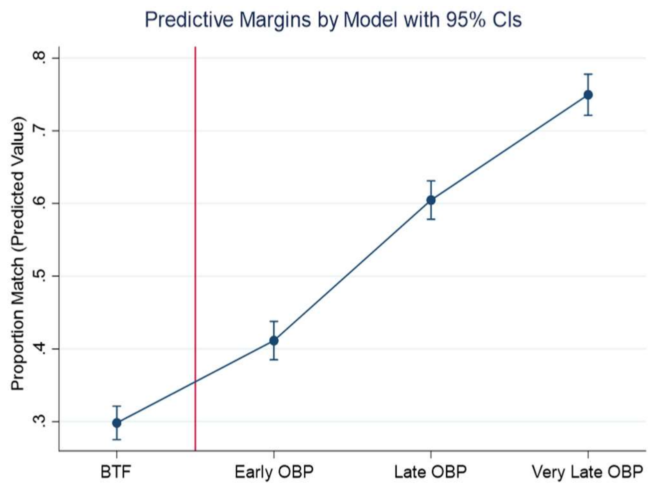
The purpose of study 2 is to compare the overall matching performance between the BTF model and the OBP model. In doing so, we used the four-level partitioning for the commitment variable while other variables remain the same. In study 1, we observed that the options in fact increase the proportion match substantially. We are interested to see if that effect is consistent across different levels of the options. We also explained earlier, that the early options call resembles the BTF model. Thus, the four-level analysis will allow us to explore both of our research questions.

TABLE 6
REGRESSION RESULTS (4X2X2)

	DV: Proportion of Match	VIF
BTF or OBP		
BTF	(Baseline)	
Early OBP	0.113***	1.35
	(0.0179)	
Late OBP	0.307***	1.35
	(0.0179)	
Very Late OBP	0.451***	1.32
	(0.0186)	
Responsiveness Low	0.0921***	1.00
	(0.0133)	
Customization High	0.0855***	1.02
	(0.0135)	
Constant	0.192***	
	(0.0157)	
Observations	630	
R^2	0.564	

We report the regression results in table 6. The result shows, when the BTF model is the baseline model, each level increase in the options call time delay constantly improves the overall matching performance. The variance inflation factors of the variables are all smaller than the threshold of 3, thus multicollinearity is not a concern in this model. We also plotted the predictive margins of the four-level commitment variable over the proportion match. As can be seen from the figure 9 below, with all factors holding constant, while the BTF model only has 0.3 overall matching, when delaying the options call time, the overall matching performance can reach up to 0.75.

FIGURE 9
PREDICTIVE MARGINS BY MODEL



Therefore, from the analysis above, we can conclude that the OBP model is a much superior model than the BTF model in that: 1) it has a substantially higher matching performance and, 2) the benefits of the OBP model is consistent across different lead-times.

The previous discussion relates to the performance of the OBP model compared to various pure-form and hybrid production models (tables 3 and 4) and conditions that maximize the benefits of real option-enabled design flexibility. Next, we see how the new OBP and original BTF model compare.

As previously developed, the BTF model can be thought of as the core of the OBP model; at least for fixed design features. However, both the OBP and BTF have the ability to postpone design commitment decisions – albeit very limitedly for the BTF model. As table 4 shows, a late design commitment enhances the effects of design flexibility.

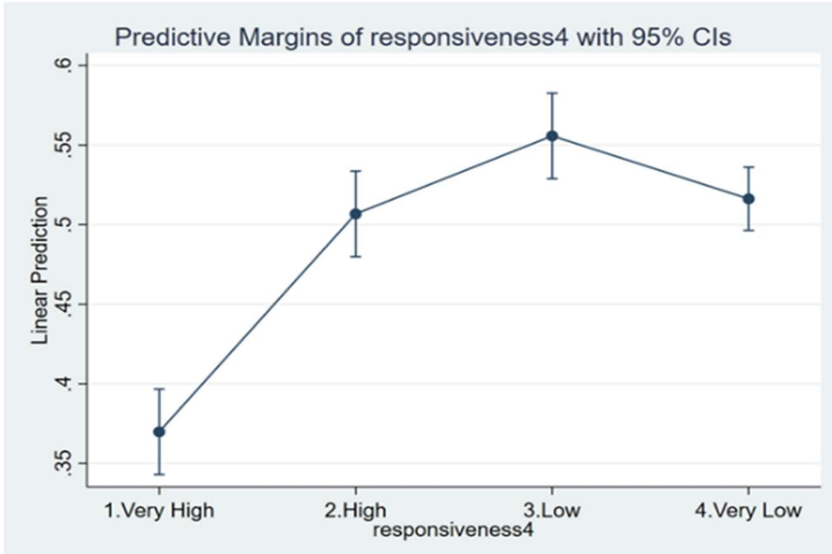
Following the regression model, Figure 9 shows the 95%CI of the predicted value for different levels of design commitment. At one extreme is the BTF model since the design is committed near build initiation. Next is what we label variously as early, late and very late OBP as defined in table 2 for the data partitions used to compare the two models.

It can be seen, that the largest improvement in match performance occurs between the levels of early and late design commitment (.411 vs .604, Δ=+46.96%), while between late OBP and Very Late OBP (.604 vs .749, Δ=+24%). The declining marginal benefit may be due to the OBP model approaching the MTO model (i.e. not much more possible improvement).

Performance Predictive Margin vs. Responsiveness

Figure 10 is the predictive margins from the regression model for the variable responsiveness. As expected, as the responsiveness requirements are reduced then the match performance improves until the condition of very low responsiveness is achieved.

FIGURE 10
MATCH PERFORMANCE PREDICTIVE MARGINS (95% CI) VS. RESPONSIVENESS



This represents a very low responsiveness condition where the customer-accepted lead time is almost the entire product build time while still not being pure form MTO. This is because the product is not committed to a specific customer order at build initiation. The long customer accepted lead-time results in a match window almost as long as the build cycle. Specifically, if customers accept very low responsiveness then the match time could start anywhere from near product build initiation until the very end of the build cycle. If a sales order arrived very early, then the environment would approximate – or duplicate – MTO and a match is more likely. However, a late-arriving sales order would be at the end of the product build cycle. While the customer may be patient, the product's flexible design features may have already expired, and thus ineligible to match. Another effect of a wide match window is that at any single time period in the match window, there may exist only a single sales order, or none, rather than multiple orders to match against multiple products – the assignment problem. Thus, instead of being a many-to-many match where the best product/order combination is created, it is a 1:m match; a single sales order can take a product that could be an even better match for an order that emerges later but cannot match because it has not arrived yet. Thus, there is an early winnowing out of the best product configurations available for later arriving orders. That is if the planner uses a "first best available match" logic as this simulation logic does.

LESSONS

In this section, we summarize the observations from study 1 and study 2 into a set of lessons. This forms a basis for discussing managerial implications.

The solution to the C-R squeeze requires that product build commence prior to the arrival of the order. When using design flexibility to reduce the effects of forecast errors in design configuration – as in the OBP model- the effectiveness of the model is underpinned by how long the flexibility lasts in the match window (i.e. how late is the call time, this is when the design is committed). This is because the arrival time of the order – while more predictable than a DP – may still arrive at different times relative to where the product is in its build cycle. Option call times can be extended by option-enabled components being in-stock (or quickly procurable) and having fast installation times.

In the C-R squeeze, the effectiveness of design flexibility is maximized (.654 vs .349, Δ=97.39%) if the option call times are late. Therefore;

Lesson 1: The effectiveness of design flexibility is maximized if the required design commitment is late.

Correspondingly, if the options have long call times (late design commitment), then, there are other advantages. Namely, the adverse effects of allowing a customer to specify many design features (i.e. high customization) are reduced. In fact, high customization in a high-responsiveness environment is beneficial (.505 vs .654, Δ=+29.5%). This is because the design is more "fluid" with fewer standard or mandatory features to degrade the matching ability of the WIP in the short match time allowed. In a more benign low response environment (late option call time), the effect of customization is low (.712 vs .735, Δ=+3.23%). This is because late option call times enable the product/order matching to more approximate MTO logic. Therefore;

Lesson 2: In a high responsiveness environment, late design commitment enables high customization to improve match performance.

and

Lesson 3: In a low responsiveness environment, late design commitment reduces the effects of customization to improve match performance.

In a pure form make-to-stock environment, the design decision is made earlier (at product build initiation) and then sold from inventory. While not a dominant production model used for the manufacturing of capital equipment, it is not always infeasible. In the case of large AC induction motors, there is "shared space" between standardized NEMA motors (<500 hp) and the larger customized – typically MTO made – motors. These motors are often the approximate size of an office desk and could conceivably be held in finished goods inventory – albeit in small quantities. They also could be modified to a limited extent quickly; primarily adding accessories – the "convertible unit" or, here, "MTS-like" case of high responsive/low-customization (table 4). The effect of early vs late design commitment is .260 vs .505, Δ=+94.2%) respectively. Thus, options enable essentially a stock product to match a larger proportion of the market demand without having to maintain a large and diverse finished goods inventory. Therefore;

Lesson 4: Options-based planning reduces (or eliminates) the need for a finished goods inventory to maintain high responsiveness.

Sometimes, a producer can influence the market (or change what market it wants to serve). This can be through marketing campaigns, incentives, or even product mix. If a producer has "market-making" power or at least the ability to choose what market it supplies then it can be seen that the maximum performance gain of using the OBP model occurs between the transition from MTS to the MTO (table 4) environment where the difference in results are (.260 vs .735, Δ=+182.7%). MTS products are often commodity-type with low profit margins and undifferentiated branding. In contrast, highly flexible design can approximate MTO customization and enable a more customized (i.e. differentiated) products which could potentially either be higher margin and/or targeted to market sub-sectors. Therefore;

Lesson 5: Options-based planning has the maximum performance premium when customization is high, and responsiveness is low.

MANAGERIAL IMPLICATIONS: ACHIEVING CUSTOMER-DRIVEN DESIGN AND RESPONSIVENESS OUTCOMES

The options-based planning model introduced in this paper uses product customization and design flexibility (real options) to address an old problem: the customization-responsiveness squeeze. However, it also presents the possibility of transforming a “problem” - the C-R squeeze - into a source of potential competitive advantage.

Figure 11 presents a conceptual framework that moves past the classic C-R squeeze, which is the focus of legacy mass-customization models like BTF and presents a vision of the future. It presents a roadmap for both future research and near-term managerial practice. It also attempts to present managers with a framework on how to respond to shortening product life cycles and increased market uncertainty where design requirements may rapidly change.

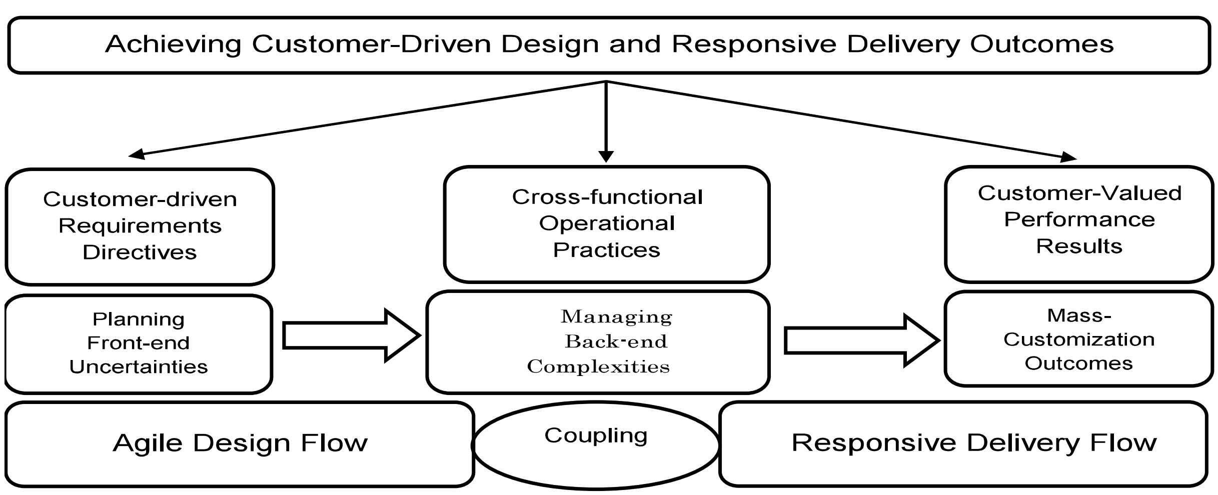
Two fundamental drivers in the current and future market of capital equipment are the need for agile design to respond to quickly changing market needs and responsive delivery to reduce the buyer risk of short-term obsolescence. Conceptually, this is the original C-R squeeze and forms the foundation of our future conceptual model. To materialize this vision, we define both supplier and customer outcomes.

For the supplier, they must engage in *planning front-end uncertainties* - specifically, anticipating possible future customer design requirements that will not become apparent until well after product build commences. The supplier must also *manage back-end uncertainties*. This is the demand uncertainty of what/if sales orders will exist at the end-stage of the product build cycle - i.e. product order matching. Maximizing the proportion of product build that ends up matched to an order at or before the end of the build is the desired *mass-customization outcome*. Specifically, products that are matched to an order will not require costly - or infeasible - holding in inventory or disposal (unsellable product).

From the customer perspective, buying capital equipment is making a strategic investment in their production/service capacity that will affect their ability to serve their own end-customers. As buyers, they have *customer-driven requirement directives* (to the equipment supplier) that reflect their own needs. Since these needs are often idiosyncratic to their own market (or firm), a standard stock product will often not suffice. Thus, there must be much more collaboration between buyer/supplier and even across functions within their own organization, what we refer to as *cross-functional operational practices*. The *customer-valued performance result* is a product that is fully customized to their specific needs and can be delivered quickly so that it can be in operation sooner and have a longer productive life before the market shifts too far and renders the equipment obsolete. The *coupling mechanism* at an operational level is real options.

The OBP model enables a supplier/customer synergy through customization that essentially enables design features to be customized without novel new technology. This could be because the customization makes use of customer-developed technology or the result of a joint development between the supplier and buyer.

FIGURE 11
CONCEPTUAL RATIONALE: ACHIEVING AGILE-DESIGN AND RESPONSIVE-DELIVERY CAPABILITIES



(Adapted from Hong, Jagani, Kim and Youn, 2019)

CONCLUSION

Addressing the customization-responsiveness squeeze requires that a product begin its build cycle prior to an actual sales order arrival. In the case of capital equipment, carry a finished goods inventory is often infeasible since a large amount of capital would be locked up and the product is physically large and often commissioned onsite at a customer location. Both the BTF and OBP mass-customization models can address the C-R as this paper has described. The primary difference between the two models is how the challenge of increasingly volatile design requirements are mitigated. For capital equipment acquisition, the responsive requirements are often less volatile because the investment decision is of a strategic nature and less subject to transient market conditions.

Because of the oftentimes-synergistic relationship between an equipment supplier and purchaser – the possibility of joint product development - it is sometimes possible to reduce the responsiveness required of the OBP model since the design configuration can be decided later in the build cycle. However, the simulation results show a possible limitation of a "first, best" product/order match logic when using a mass-customization model like OBP. Future research can model scenarios where the planner withholds product order matches to mitigate this poaching of highly flexible products meeting orders that could possibly have been served later. However, this presents the "match or wait" dilemma described in Akinc & Meredith (2009) whereby a match is withheld but no later eligible order arrives (i.e. product not configured correctly for the later arrive order). The authors make an analogy to an everyday situation, the "parking lot" problem where one forgoes a distant spot in the hope of a closer spot that may not be available.

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