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Factorial Model Design for Business Process Variables

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Abstract

The dynamic corporate environment has resulted in enterprise practitioners exploring optimal measures towards enhancing business sustainability and competitiveness. The statistical factorial technique is effective for experimenting with business process variables resulting in the optimal execution of business processes. An ideal factorial model design integrates business process variable variations, main effects together with interactions. A factorial model for predicting the impacts of business process variables on business processes is developed. Factorial methodologies serve as an effective tool for simulating scenario responses. The scenarios result in the desired response based on selected business variable effects and interactions. A framework for setting and adjusting a series of selected independent business process variables to obtain a dependent response (business process turnaround time) is developed. The factorial model allows for configurations of defined key performance identifiers based on selected defined metrics to quantitatively determine effects of each business process variables on enterprise operations.
This research develops a factorial model design for predicting and evaluating what effect changing or combining business process variables would have on corporate operations. A factorial model case effectively quantifying impacts of selected business process variables on business change is developed. Results present a ranked layout of business process variable impacts on business processes based on distinct effects and interactions. Developed factorial model is efficient for large multinationals exploring the current and future status of business processes based on the impacts of selected business process variables.

Keywords
Business processes, Business process variable, Factorial model.

1. Introduction

Business sustainability is an essential driver to large multinationals (Jeston & Nelis, 2014 and Houy, et.al, 2010). This business paradigm refers to global best practice measures employed by corporate entities towards meeting present and future benchmark protocols relative to the execution of business functions (Thomas & Katrin, 2015). Business operations of large multinationals are captured based on business processes. Business processes are described as the collaboration of business functions (Bradford & Gregory, 2015). The literature (Medoh & Telukdarie, 2016) is prioritized in this research with limitations to developing an optimal statistical testing framework of business process variables. Medoh & Telukdarie developed a predictive model for understanding and testing the impacts of numerous essential business process variables on corporate functions. A framework for simulating the impact of business change via business process simulation and modelling techniques is explored. The research identified limitation in comprehensively developing an effective statistical experimental protocol for exploring business process variable effects on business processes. This research extends previous literature introducing statistical factorial techniques for comprehensively exploring impacts of distinct business process variables. An effective and efficient statistical framework for predictive testing and experimental protocols based on global best practices is developed.

Based on the limitation identified in previous literature, this research conceptualizes for an optimally designed business process variable framework via statistically defined predictive equations adopting design of experiment methodologies. The design of experiment method is an effective optimization technique which supports several optimization protocols (Kumar, 2017). This research substantiates on the following objectives:

- Obtain an estimated business process variable effects.
- Investigate for maximum responses on business process variable effects.
- Investigate for maximum responses on a combination of business process effects.
- Define an optimal predictive equation for business process variables.

This research explores on detailed objectives to develop a factorial model to predict and evaluate the effect that a change or combination of business process variables will have on business operations. A detailed list of business process variables aligned with unique identifiers is presented in literature (Medoh & Telukdarie, 2017). These business process variables are inclusive of Human resource resolution time, Escalation rate, System maturity index, Business state index, System resolution time, Critical factor, Cost, Value chain design, Operational tracking, Completeness of processes, Integration¸ Data/inventory, Automation, Efficiency/Energy, Skills, Standard and Non-standard, Change and Environmental technologies. These business process variables though comprehensive can be extended to future research. Selected business process variables from the list detailed ls explored to present a factorial model application case as an illustrative example.

2. Background Context

A factorial model design is a design of experiment method with more than one factor (independent variables). A relation presenting sets of interaction columns equivalent in the design matrix is defined. An interaction exists between business variables if the effect of one business variable varies across the different levels relative to the other business variables. The design matrix is developed in columns of signs (+, -) denoted by treatment combinations (I). The positive (+) sign denotes business process variable at a high level while negative (-) sign denote business process variable at a low level. This defines the level each business variable is to be held for distinct experimental iteration. Literature present application scenarios of the full and fractional factorial model design in Engineering, manufacturing processes, business and management (Landsheer, & van den Wittenboer, 2015; Bergquist, 2015; Montgomery & Runger, 2006; Elshennawy, 2004).

A full factorial model is a statistical design of two or more factors that explores the response for all possible combinations based on the input factors (Vichi & Hal, 2001). A fractional factorial model is based on an alias structure generated from a full factorial design (Hongguan & Wu., 2001). The fractional factorial design such as the Taguchi fractional factorial method reduces the number of experimental runs of large input factors (Jaharah, et.al, 2013). The Taguchi fractional factorial experiments adapt orthogonal arrays to present an alternative to full factorial designs (Taguchi, *et.al.* 2004). Input factors and interactions are aligned to the orthogonal array columns via linear graphs (Sahin, 2005). Selecting an efficient orthogonal array effective for a large number of business process variables presents a challenge. The Taguchi methodologies are adapted in future research to develop a fractional factorial model design for exploring comprehensive business process variables detailed in (Medoh & Telukdarie, 2017). This present research develops a full factorial design of three selected business process variables. The design results to a paradigm ensuring the optimization of business processes. Business process optimization describes measures explored towards investigating for conditions that present minimum or maximum value of a defined response (Van Der, et.al, 2016 and Balko & SAP, 2013). The collaborated steps considered in exploring the full factorial techniques is presented in Figure 1.

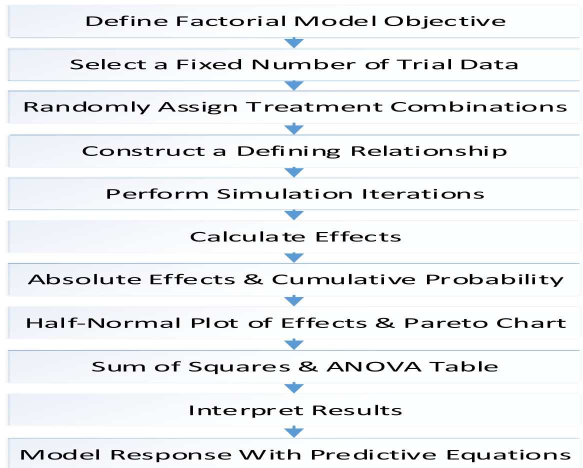

Figure 1. Full factorial steps adapted from (Bergquist, 2015)

3. Application Model

This section presents an application model based on the factorial methodologies to develop a full factorial model design of business process variables. Considering two factors A and B, factors denote independent business process variables presented in a "A x B" notation. Where "A" defines the number of levels of one independent variable and "B" the second independent variable. The main Effect is the effect of one factor on the response (dependent variable). An interaction occurs when the effect of a factor on the response changes. This is dependent on the level of another factor. Factor analysis presents a framework for estimating a model explaining the variance or co-variance between sets of observed factors by a set of fewer unobserved factors and weightings (performance identifiers).

This research investigates three business process variables (Table 1) from the comprehensive list of business process variables detailed in (Medoh & Telukdarie, 2017) to present a factorial application case. Justification together with supporting literature for adapting each business process variable aligned with unique performance identifiers is defined in (Medoh & Telukdarie, 2017). The full factorial design experiments are conducted on logistics business process variant steps database developed in (Medoh & Telukdarie, 2016). The steps adapted to develop a full factorial model design for business process variables is explored in the following subsections.

Step 1: Define factorial model objective

Develop a factorial model design based on business process variables "System resolution time (A)", "Automation (B)" and "Business state index (C)".

Step 2: Select a fixed number of trial data

A fixed number of factor levels based on sets of performance constraints is selected for screening the experiment based on (I) controlled factors. Experimental iterations for all combinations of levels based on the factor results to n1 levels of factor 1, n2 levels of factor 2 and so on. The factorial design is thus n1 * n2 * … * ni (where i = infinity). A modified business process variable experimental values and performance identifiers for the three investigated business process variables as adapted from (Medoh & Telukdarie, 2016) is presented in Table 1 & 2. This data is obtained from a detailed reviewed simulated process from business sectors.

Table 1. Business process variable experimental values

ACRONYM	FACTOR	LOW LEVEL (-)	NORMAL (N)	HIGH LEVEL (+)
A	System Resolution Time	1.0	1.05	1.1
B	Automation	0.8	1.0	1.2
C	Business State Index	1.0	1.2	1.4

Table 2. Performance identifiers

S/N	BUSINESS VARIABLE	IDENTIFIERS	
1	Automation	No Automation	0.8
		Partially Enabled Automation	1.0
		Fully Enabled Automation	1.2
2	System Resolution Time	Full SLA Less Than 2HRS	1.0
		Full SLA Less Than 4HRS	1.05
		Partial SLA Less Than 6HRS	1.1
3	Business State Index	Greater Than 2Yrs Last Changed	1.0
		Less Than 2Yrs Last Changed	1.2
		Less Than 1Yr Last Changed	1.4

Step 3: Randomly assign treatment combinations

Randomly assign treatment combinations as presented in Table 3. Small letters denote treatment combinations while capital letters denote effects and factors. A "+" and "-" sign is indicated under business variables A, B and C columns. This corresponds to the level each business variable is to be held for distinct experimental iteration. The signs in the interaction columns are calculated by taking the product of the signs in the associated A, B and C columns. The response (Y) column shows the simulated values of business variables held at distinct business level respectively based on distinct row effect and interactions.

Step 4: Construct a defining relationship

Construct a defining relationship for determining the effects of the business process variable interactions. The interactions of three (AC, AB, BC) 2-factor interactions and one (ABC) 3-factor interactions is explored. Summation of the interaction effects together with the main factor effects results to a total of seven effects as presented in Table 3.

Table 3. Treatment combinations and simulation experimental results

Level	Treatment combination	Factor			2-factor interaction			3-factor interaction ABC	Response (Y)
		A	B	C	AB	AC	BC		
1	(I)	-	-	-	+	+	+	-	Y1
2	a	+	-	-	-	-	+	+	Y2
3	b	-	+	-	-	+	-	+	Y3
4	ab	+	+	-	+	-	-	-	Y4
5	c	-	-	+	+	-	-	+	Y5
6	ac	+	-	+	-	+	-	-	Y6
7	bc	-	+	+	-	-	+	-	Y7
8	abc	+	+	+	+	+	+	+	Y8

Symbol (I) represent treatment combinations where all main business process variables are at low levels. At a high level, a small letter representing business variable appears in the treatment combination symbol while at a low level, it does not appear.

Step 5: Perform simulation iterations

Business processes are iterated based on treatment combinations illustrated in Table 3 to obtain a response. This research selects "transportation incident request" presented in Figure 1 as a case study business process to present an application scenario.

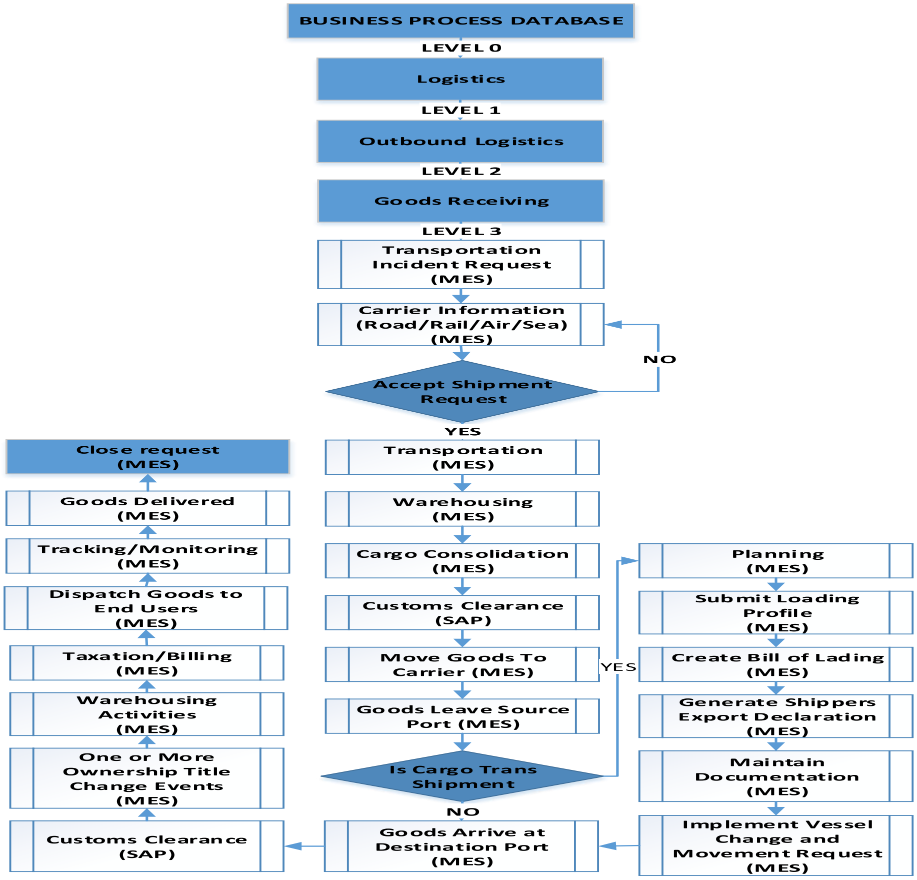

Figure 2. Logistics business process database

The Accuprocess business process modeler is utilised in developing and configuring a repository representation together with simulating transportation incident request business processes. Results from the simulation scenarios are presented in Table 4.

Table 4. Data for responses

LEVEL	RANDOMISED RUN (RR)	A	B	C	RESPONSE (Y)
1	8	(-)	(-)	(-)	1051.3
2	6	(+)	(-)	(-)	1047.1
3	4	(-)	(+)	(-)	1057.3
4	2	(+)	(+)	(-)	1056.6
5	1	(-)	(-)	(+)	1053.3
6	3	(+)	(-)	(+)	1013.7
7	5	(-)	(+)	(+)	1023.3
8	7	(+)	(+)	(+)	1050.2
EFFECT		-4.4	5.5	-18	

Step 6: Calculate effects
This is obtained by calculating average of high levels (+) to average of low levels (-) based on simulation response. The average change in simulation response caused by changing levels of the business variables is obtained. Results from effects are presented in Table 5.

Table 5. Matrix of effects and interactions

FACTOR	EFFECT
A	-4.4
B	5.5
C	-18
AB	17.5
AC	-1.95
BC	-2.25
ABC	15.75

This research infers from Table 5, that the impact of A has the minimal effect on the response while the impacts of B and C are much larger effects relative to the response obtained. The next step is investigated to ascertain if all the effects vary normally. The graphs for main effects and interactions effects is illustrated via a half normal plot and Pareto chart of effects presented in Figure 3 and 4.

Step 7: Absolute effects and cumulative probability
Sort absolute value of effects in ascending order and Calculate Probability values Pi from the formula. Results are presented in Table 6.

Table 6. Absolute effect and cumulative probability of effect

FACTOR	ABSOLUTE EFFECT (ASCENDING ORDER)	CUMULATIVE PROBABILITY (14.28)%
AC	1.95	7.14
BC	2.25	21.42
A	4.4	35.7
B	5.5	49.98
ABC	15.75	64.26
AB	17.5	78.54
C	17.95	92.82

Step 8: Half-normal plot of effects and Pareto chart
Plot effects and determine significant effects off the line (model) together with a fit line through near-zero points (residual) adopting the Pareto chart. The half-normal plot and Pareto chart are presented in Figure 3 and 4.

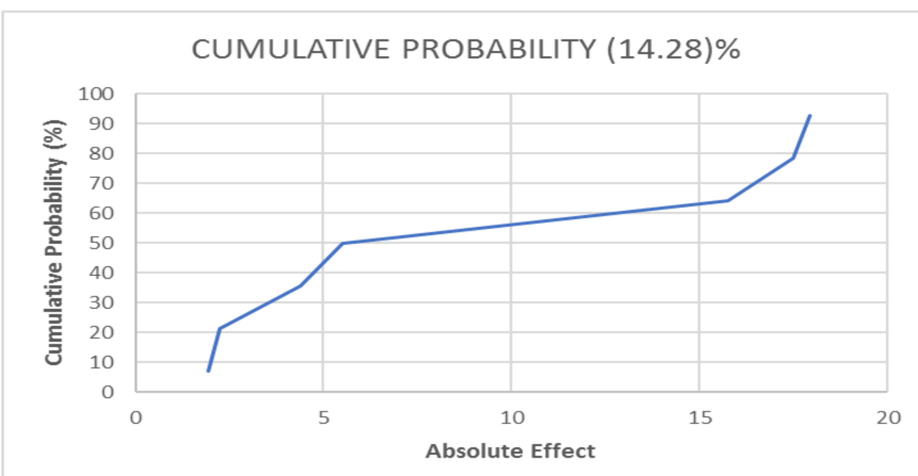

Figure 3. Half-normal plot

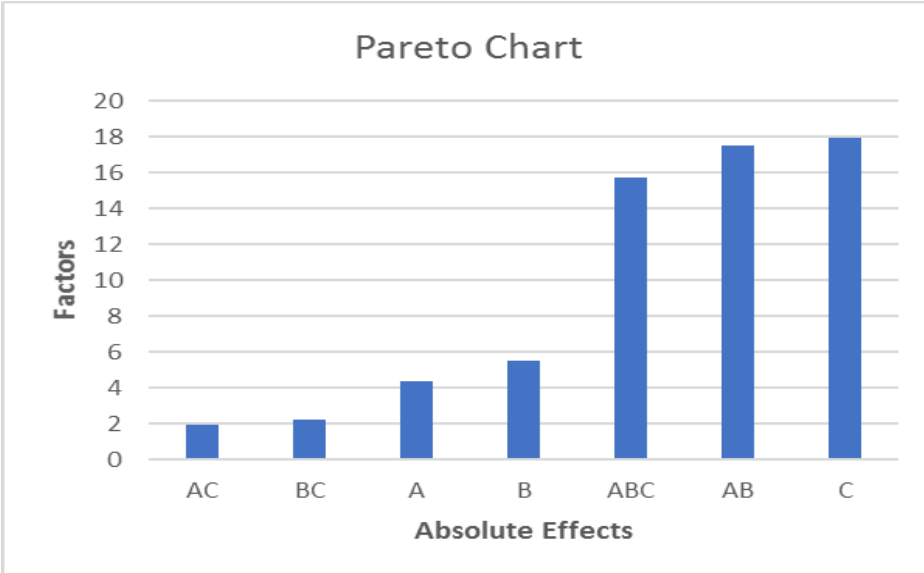

Figure 4. Pareto chart

The half-normal plot (Figure 3) illustrates the essential factors inclusive of interactions. This is calculated by quantitatively estimating effect of a defined main effect or interaction and the rank relative to other main effects and interactions. The calculation is based on the least squares estimation technique. The Pareto chart (Figure 4) presents the absolute values of the standardized effects from the largest effect to the smallest effect. The magnitude and importance of the factor effects is illustrated. Aligning with output presented in Figure 3 and 4, this research considers the significant effects (model) to be factors “B”, “C” and “BC” while the residual constituents are factors “A”, “AB”, “AC”, and “ABC”.

Step 9: Sum of squares and ANOVA table

Evaluate each effects sum of squares (SS) from formula and determine SSmodel (Table 7) together with SSresidual (Table 8). An ANOVA table is designed to estimate p-values, this statistically verifies all responses. The points aligning with statistically control limits is adapted for the model.

Table 7. Data for SSmodel

SS (B)	SS (C)	SS (BC)
60.5	644.41	10.13

Table 8. Data for SSresidual

SS (A)	SS (AB)	SS (AC)	SS (ABC)
38.72	612.5	7.61	496.13

The sum of squares presents a framework for evaluating the increase in variance effects of the factors. This results to an ANOVA table which presents statistics data utilized for hypothesis testing relative to the populated means.

Step 10: Interpret results.

Determine the degree of freedom, mean square together with F value of selected business process variables (Table 9). If the actual F value (calculated) exceeds the critical F value (statistical table) at an acceptable risk value, the null hypothesis is rejected.

Table 9. Data for F-values

Source	Sum of Squares	Degree of Freedom	Mean Square	F Value	Output
Model	715.03	3	238.34	0.83	Reject
B	60.5	1	60.5	0.21	Reject
C	644.41	1	644.4	2.23	Reject
BC	10.13	1	10.13	0.04	Reject
Residual	1154.95	4	288.74		
C or Total	1869.98	7			

Step 11: Model response with predictive equations

Experimental results are adapted to develop a mathematical model representing the effects of business process variables on business processes (Table 10). The coefficients for each effect and interaction is determined based on a representative equation. The predictive equation is based on a 95% statistical significance confidence for the interactions and effects. At this confidence level, effect A together with interactions AB and AC are found to have no statistically significant effect on response. This effect and interactions are removed from the predictive equation representing the effects of business process variables "A", "B", and "C" on business processes. Literature presents a factorial generalized predictive equation in the form "$Y = ƛ0 + ƛ1B + ƛ2C + ƛ12BC$" (Mark & Patrick, 2007). Where "Y = predictive response", "ƛ0 = intercept", "ƛ1 = model coefficient of factor B", "ƛ2 = model coefficient of factor C", and "ƛ12 = model coefficient of factor BC".

Table 10. Predictive equation table

Predictive Response (Y)	Turn Around Time
Intercept (ƛ0)	1044.1
Model Coefficient of Factor B (ƛ1)	2.75
Model Coefficient of Factor C (ƛ2)	-8.98
Model Coefficient of Factor BC (ƛ12)	-1.13

Aligning with turnaround time outputs presented in table 10, the research defines a factorial predictive equation for investigated business process variables formulated in equation 1.

$$Y = 1044.1 + 2.75B - 8.98C - 1.13BC \text{ ……………………… eqn. 1.}$$

Equation 1 is adapted to predict the effects of interactions on the response (Y) for the three investigated business process variables. The intercept (ƛ0) represents the line gradient indicating a rise in response (effect) divided by corresponding factor level iterated. The value 1044.1, therefore, indicates the mean of all actual responses.
The model coefficient of factor B (ƛ1) and BC (ƛ12) are adapted to quantify the relative effects of the factors on the response (Y). The research infers from equation 1, the coefficient value of B "2.75" significantly generates a greater effect compared to the coefficient value of C "- 8.98" on the response.

Conclusion

This research presented an application scenario model design on the adaption of factorial techniques in predicting and evaluating the effects of business process variables on business processes. The research developed a factorial model to predict and evaluate the effect that a change or combination of business process variables will have on business operations. The application case explores the viability of factorial techniques to investigate business process variables based on defined unique metrics and identifiers. The full factorial technique is adopted in this research for exploring the application scenario. The output presents the optimal effects and interactions of selected business process variables. A representative predictive equation of the optimal effects and interactions is presented. This research document serves as an improvement to (Medoh & Telukdarie, 2016) presenting a factorial model or design of test case business process variables. The business process variables investigated are "System Resolution Time (A)", "Automation (B)", and "Business State Index (C). The research demonstrated factor effects B and C together with interaction effects BC are significant. Future research is essential in developing an application model exploring a comprehensive list of business process variables detailed.

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