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นาย ปิยนัยน์ กลิ่นน้อย

APPLICATION OF EXPERIMENTAL DESIGN AND RESPONSE SURFACE
METHODS FOR FIELD PRODUCTION FORECAST

Mr. Piyanai Klinnoi

A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Engineering Program in Petroleum Engineering
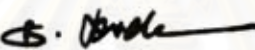Department of Mining and Petroleum Engineering
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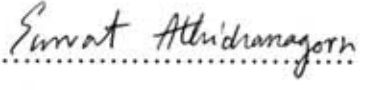
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ปิยนัยน์ กลิ่นน้อย : การประยุกต์ใช้การออกแบบการทดลองและผลตอบสนองแบบโครงร่างพื้นผิวเพื่อทำนายผลผลิตจากแหล่งผลิต (APPLICATION OF EXPERIMENTAL DESIGN AND RESPONSE SURFACE METHODS FOR FIELD PRODUCTION FORECAST) อ.ที่ปรึกษา : อ.ดร. จิรวัฒน์ ชีวรุ่งโรจน์, อาจารย์ที่ปรึกษาร่วม : ดร. ทศพล ไชยอนันต์สุจริต, 90 หน้า

การทำนายผลผลิตจากแหล่งผลิตมีความสำคัญต่ออุตสาหกรรมน้ำมันและก๊าซ ซึ่งมีส่วนช่วยในการประเมินทางด้านเศรษฐศาสตร์และช่วยในการวางแผนสำหรับการผลิต เพื่อให้ตอบสนองกับจุดมุ่งหมายทางธุรกิจ

อย่างไรก็ตามมีตัวแปรหลายตัวที่มีผลกระทบต่อการผลิตไฮโดรคาร์บอน เช่น คุณสมบัติของหินและคุณสมบัติของไฮโดรคาร์บอน เป็นต้น โดยตัวแปรเหล่านี้มีความผันผวนซึ่งจะส่งผลลัพธ์ต่อความแปรปรวนในอัตราการผลิต ดังนั้นในการทำนายผลผลิตจึงต้องทำความเข้าใจกับปัจจัยเหล่านี้ด้วย

วิธีการออกแบบการทดลองเป็นทางเลือกหนึ่งในการวิเคราะห์ความแปรปรวน แนวคิดพื้นฐานคือการเปลี่ยนแปลงค่าของตัวแปรหลายตัวพร้อมกัน เพื่อที่ให้ได้ข้อมูลมากที่สุดในขณะเดียวกันใช้กระบวนการน้อยที่สุด ผลลัพธ์จากการทดลองจะถูกนำมาสร้างแบบจำลองทางคณิตศาสตร์ ซึ่งสามารถใช้เป็นตัวแทนในการคำนวณได้

วิทยานิพนธ์ฉบับนี้เป็นการศึกษาและพัฒนาวิธีการทำนายการผลิตก๊าซ โดยใช้เทคนิคการออกแบบการทดลองและผลตอบสนองโครงร่างพื้นผิวด้วยการสร้างแบบจำลองตัวแทนในการคำนวณผลผลิตแทนที่การใช้แบบจำลองในคอมพิวเตอร์ในส่วนของการคำนวณ กระบวนการคัดกรองตัวแปรได้ทำเพื่อที่จะบ่งชี้ถึงตัวแปรที่มีผลกระทบสูงเพื่อที่จะนำไปสร้างแบบจำลองตัวแทนในการทำนายการผลิตก๊าซ จากผลลัพธ์พบว่าแบบจำลองตัวแทนการผลิตที่ได้มีความแม่นยำสูง ซึ่งเราสามารถใช้แบบจำลองของการผลิตในการทำนายผลผลิตในแหล่งอื่นๆซึ่งมีคุณสมบัติคล้ายกันได้

ภาควิชาวิศวกรรมเหมืองแร่และปิโตรเลียม   ลายมือชื่อนิสิต...

สาขาวิชาวิศวกรรมปิโตรเลียม   ลายมือชื่ออาจารย์ที่ปรึกษา..................................

ปีการศึกษา 2550   ลายมือชื่ออาจารย์ที่ปรึกษาร่วม..............................

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KEY WORD : /EXPERIMENTAL DESIGN/PRODUCTION FORECAST

PIYANAI KLINNOI: APPLICATION OF EXPERIMENTAL DESIGN AND RESPONSE SURFACE METHODS FOR FIELD PRODUCTION FORECAST. THESIS ADVISOR: JIRAWAT CHEWAROUNGROAJ, Ph.D., THESIS CO-ADVISOR : THOTSAPHON CHAIANANSUTCHARIT, Ph.D., 90 pp.

Production forecast is an essential part of the oil and gas industry. It is not only the important part of any economic evaluation but also planning operation schedule in order to sustain production rate to meet business target.

However, there are many factors affecting the hydrocarbon production rate, e.g. rock properties and hydrocarbons properties, these factors can widely vary which result in production rates variation. Therefore, a production forecast must be based upon an understanding of these factors.

Experimental design method is an alternative to traditional sensitivity analysis. The basic idea behind this methodology is to vary multiple input parameters at the same time such that the maximum information can be obtained at the minimum process.

This thesis developed gas production forecast technique using application of experimental design and response surface methods by representing the integrated production modeling simulation with a surrogate model. Parameters screening process was done to identify the high effect parameters. Surrogate model for gas production forecast was developed. From the result it shows that the model has high accuracy in production estimation.

Department: Mining and Petroleum Engineering   Student's Signature...................

Field of study: Petroleum Engineering   Advisor's Signature...................

Academic Year: 2007   Co-advisor's Signature...................

ACKNOWLEDGEMENTS

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NOMENCLATURE

B_o	oil formation volume factor
B_g	gas formation volume factor
B_w	water formation volume factor
C_w	water compressibility
c_f	rock pore volume compressibility
CCC	central composite circumscribed
CCI	central composite inscribed
CCF	central composite face centered
DOE	design of experiment
m	ratio of gas cap pore volume to oil pore volume
N_p	cumulative oil production
N	initial oil in place
$OVAT$	one variable at a time
p	average reservoir pressure
Q	flow rate
R_s	solution gas-oil ratio
R_p	cumulative production gas-oil ratio
RSM	response surface methodology
S_w	water saturation
W_e	cumulative aquifer influx
W_p	total water produced

GREEK LETTER

α	distance from the center of the design space to a star point
ε	random error
ϕ	porosity

CHAPTER I

INTRODUCTION

Generating production forecasts are an essential part of the oil and gas industry. Production forecasts are used for preparation of any economic evaluation. And it is helpful for planning operation schedule in order to sustain production rate meeting business target. It is accomplished by evaluating the past, investigating current conditions and projecting these into future based upon the best information in hand at that time.

There are many factors effect the hydrocarbon rate which is produced from wells and fields. The geologic factors, i.e., type and characteristics of the rock, true vertical depth, measuring depth, pay thickness, properties of the hydrocarbons and also including completion techniques and methods of production, affect production rates. And these factors can vary widely. Hence, production rates will also vary widely. Therefore, a production forecast must be based upon an understanding of these factors.

Reservoirs in the Gulf of Thailand are typically complicated. Commingle well, well contains more than one pay sand, always found. Necessary data for reservoir simulation task was unable to obtain completely. So, production forecast by using reservoir simulation is tough to be done.

"P Field" is one of the major gas fields in the Gulf of Thailand. This field started operation in 2003. And we will assign this field as base field in order to develop production forecasts technique by using data obtained from this field.

This thesis will develop production forecast technique by application of experimental design and response surface methods. These methods have been shown to have significant potential in production forecasting and ultimate recovery estimates by representing the numerical reservoir simulation with a surrogate model.

Petroleum Experts have developed the integrated production modeling toolkit (IPM) which contains three main parts namely GAP, MBAL and Prosper. These tools can model the complete production system from the reservoir to the surface network. GAP is a multiphase optimizer of the surface network which links with PROSPER

and MBAL to model reservoir and productions system. GAP can model production system containing oil, gas and condensate, in addition to gas or water injection systems the engineer is able to design complex field models. The reservoirs, wells and complete surface systems model, having been matched for production history, will accurately optimize the entire network and run predictions. Hence, IPM is selected as our simulator.

1.1 Outline of Methodology

This study starts with obtaining field data which includes reservoir data and production system data from the reservoir to the surface and then constructing the GAP model which will be used as process model. Next, parameters of interest and their statistical distribution will be determined for experimental design approach.

Screening, the aim is to identify the input variables that have the largest impact in the result of the process. One variable at a time (OVAT) method and Plackett-Berman design, two levels design, are selected methods to design a series of input variables for screening purpose. Then, Pareto chart which describes the effects of each variables to output are used as a tool for selecting the high effect variable to the next step.

Perform 3-level design for the key variables to estimate in more detail of response. Then, the response will be fitted by regression method, interpolation method as a surrogate model for the response.

Perform history matching for the surrogate model with historical data in order to check the quality of the model. The tasks will be performed as flowcharts in figure 1.1.
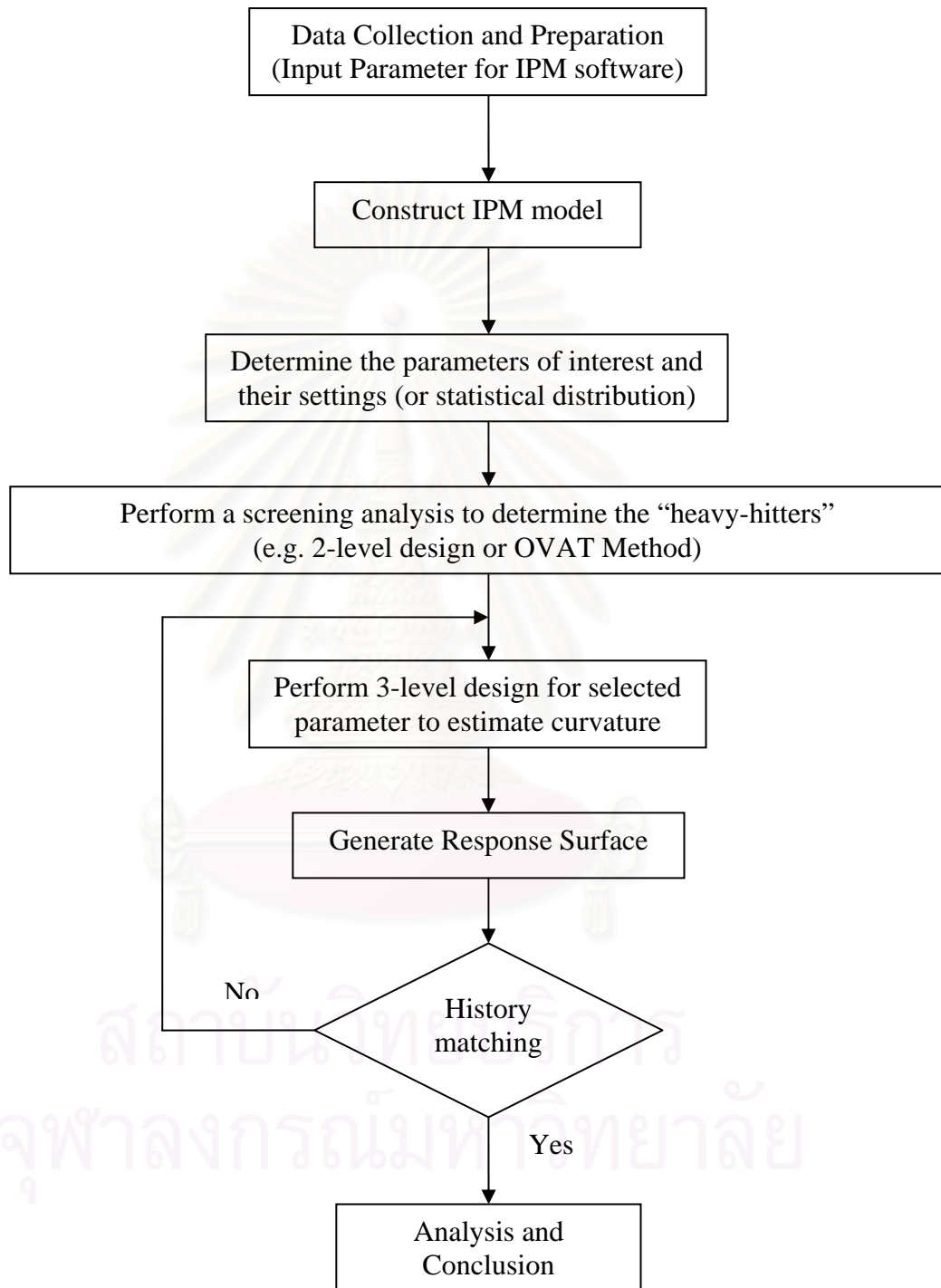
Figure 1.1: Thesis study workflow.

1.2 Thesis Outline

This thesis paper consists of six chapters.

Chapter II reviews previous works on application of experimental design and response surface concerning to this study.

Chapter III presents the experiment design technique which allows screening the high effect variables and obtaining the maximum information at a minimum process of experiment. This chapter also presents response surface method explores the relationships between several explanatory variables and one or more response variables or output from experiment.

Chapter IV introduces the integrated production modeling toolkits which is used as simulator for this research and its theory behind.

Chapter V presents methodology and results of this study. This chapter will study and obtain general information of the selected field in order to define in more detail about simulation methodology. This chapter also describes the steps and details involved in simulation model construction and describe methodology for experimental design, response surface methodology approach then discusses results from its application.

Chapter VII presents the conclusion and provides recommendation for future works.

CHAPTER II

LITERATURE REVIEW

The technique of experimental designs and response surface were applied by many authors for oil and gas application. This chapter discusses some of selected previous works which applied appropriate experimental design and response surface for a specific purpose and summarizes typical workflow to apply experimental design and analysis efficiently.

Chewaroungroaj[3] demonstrated several approaches that qualitatively estimate uncertainty in specific hydrocarbon recovery predictions. His approaches include scaling, first-order Analysis, second-order Analysis, and the Taguchi and Box-Behnken experimental designs. From the results, experimental design can provide a reasonably accurate uncertainty estimation of hydrocarbon recovery with fewer simulation runs than Monte Carlo simulation. And response surface also applied for developing and optimizing processes.

Peake[4] presented the paper that identifies key subsurface uncertainties impacting waterflood performance and quantifies uncertainty with P10/P50/P90 oil forecasts for Minagish reservoir. Experimental design techniques were used to establish the minimum simulation runs needed to quantify uncertainty. Analysis of variance and multiple linear regressions were used to identify the most significant uncertainties and to create a proxy for simulator. The proxy was used in Monte Carlo simulation to develop P10/P50/P90 oil forecasts.

Cheong and Gupta[5] presented the paper that investigates the feasibility of experimental design and analysis methods by using three examples including oil in place equation, excel spreadsheet for oil in place, and multiple deterministic modeling of a fluvial reservoir- Mungaroo formation. It includes discussions and guidelines on how to select efficient design by using expert knowledge and a decision tree, and how the experimental response can be fitted accurately with the response surface method to develop a good surrogate equation.

Table 2.1 is summarized by Cheong[5] to show presented papers that a variety of experimental design/methodologies have been proposed and tested for oil and gas applications.

Table 2.1 summary of the EDA methods: applications in oil/gas reservoirs

	Year	Objective of Studies: 1 = Sensitivity (screening), understand experimental behaviour, history matching etc.; 2 = Predict the output response & distribution curve; 3 = Optimisations (e.g. field developments etc.)			Response(s): 1 = HCIIP; 2 = Reservoir or Well Production Behaviour (UR, Water Breakthrough Time etc.); 3 = Others			Plackett-Burman	2^{k-p} fractional factorial design (FFD)	3^{k-p} FFD	2^k and/or 3^k full factorial	Central Composite	Box-Behnken	Mixed 2-, 3- and/or 4-level full factorial	D-optimal	Latin Hypercube (LHD) or modified LHD etc.	Other designs (Taguchi etc.), modified designs etc.	Replications of design matrix for stochastic effects	Response surface or Regression Methods	Kriging (K) or Joint Modelling Method (J)	Evaluation of the fitted equation with test runs
		1	2	3	1	2	3														
Sawyer et al.[1]	1974	■				■													■
See & Horne[2]	1983	■		■		■									■			■	
Chu[3]	1990		■			■									■			■	
Damsleth et al.[4]	1991	■				■									■		■		
Egeland et al.[5]	1992	■				■											■		
Kjønsvik et al.[6]	1994	■				■		■									■		
Aanonsen et al.[7]	1995	■				■									■	■	■	K	■
Sandsdalen et al.[8]	1996	■				■									■		■		
Tyler et al.[9]	1996	■		■		■											■		
England & Townsend[10]	1997	■			■												■		
Jones et al.[11]	1997	■		■		■								■			■		■
England & Townsend[12]	1998	■				■											■		
Dejean & Blanc[13]	1999	■				■			■						■		■		
Narayanan et al.[14]	1999	■				■								■			■		
Vincent et al.[15]	1999	■				■				■				■			■		
Chewaroungroaj et al.[16]	2000	■				■			■	■				■			■		
Corre et al.[17]	2000	■				■			■								■		
Guerrero et al.[18]	2000	■				■			■								■		
van Elk et al.[19]	2000	■				■						■					■		
Venkataraman[20]	2000	■				■						■					■		
Brandsæter et al.[21]	2001	■				■										■	■		
Charles et al.[22]	2001	■				■					■						■		
Manceau et al.[23]	2001	■				■					■						■		
White et al.[24]	2001	■				■			■	■							■		
Zabalza-Mezghani et al.[25]	2001a	■				■			■								■	J	
Zabalza-Mezghani et al.[26]	2001b	■				■			■								■	J	
Friedmann et al.[27]	2001	■				■		■									■		■
Novakovic et al.[28]	2002	■				■			■								■		
Jian et al.[29]	2002	■				■			■								■		
Kabir et al.[30]	2002	■				■			■	■							■		
Kumar[31]	2002	■				■			■	■							■		

Note: ■ = YES

Table 2.1(continued) summary of the EDA methods: applications in oil/gas reservoirs

	Year	Objective of Studies: 1 = Sensitivity (screening), understand experimental behaviour, history matching etc. 2 = Predict the output response & distribution curve 3 = Optimisations (e.g. field developments etc.)			Response(s): 1 = HCIIP; 2 = Reservoir or Well Production Behaviour (UR, Water Breakthrough Time etc.); 3 = Others			Placket-Burman	2^{k-p} fractional factorial design (FFD)	3^{k-p} FFD	2^k and/or 3^k full factorial	Central Composite	Box-Behnken	Mixed 2-, 3- and/or 4-level full factorial	D-optimal	Latin Hypercube (LHD) or modified LHD etc.	Other designs (Taguchi etc.), modified designs etc.	Replications of design matrix for stochastic effects	Response surface or Regression Methods	Kriging (K) or Joint Modelling Method (J)	Evaluation of the fitted equation with test runs
		1	2	3	1	2	3													
Queipo et al.[32]	2002a		■			■										■			K	■
Queipo et al.[33]	2002b		■			■										■			K	■
Queipo et al.[34]	2002c		■			■					■								K	■
Vincent et al.[35]	2002	■	■			■							■					■		
Wang & White[36]	2002		■			■						■						■		■
Badru and Kabir[37]	2003	■	■			■										■			K	■
Berg et al.[38]	2003	■	■			■							■							
Cheong & Gupta[39]	2003	■				■			■		■					■		■		■
Feraille et al.[40]	2003	■	■			■			■						■			■		■
Friedmann et al.[41]	2003	■	■	■		■			■						■			■		
Landa & Güyagüler[42]	2003	■	■			■					■				■				K	
Li & White[43]	2003	■	■			■					■						■			
Portella et al.[44]	2003	■	■	■		■			■		■							■		
Sahni[45]	2003	■	■			■			■									■		
White & Royer[46]	2003	■				■			■									■		
Cheong & Gupta[47]	2004	■				■					■							■	K	
Smith et al.[48]	2004	■	■			■			■							■		■		
Zabalza-Mezghani et al.[49]	2004	■	■	■		■			■					■		■		■	J	
Zerpa[50]	2004	■	■	■		■								■				■	K	

Note: ■ = YES

From the previous studies we can conclude that to apply the experimental design and analysis methods efficiently, a typical workflow includes.

1) Pre experimental planning

   Expert knowledge is required for preparing a list of input uncertainties including their interrelationships (e.g. dependency)

2) Experimental design

   Screening objective (optional) – the purpose of the experiment is to select or screen out the few important main effects from the many less important ones.

   Response surface objective – the purpose of the experiment is to capture the significant quadratic effects for prediction purposes or to increase the design runs to accommodate more potential effects

3) Analysis of experiment

   In this section, the design matrices of experiment and its individual results are fitted by mathematical model to develop a surrogate model.

4) Applications

   The surrogate model, developed in the previous section, can be used for sensitivity studies and predicting results.

The next chapter will describe in more detail and provide clearly understand in experimental design and response surface technique which has been applied for this research.

CHAPTER III

EXPERIMENTAL DESIGN
AND RESPONSE SURFACE

Engineers and scientists often perform one variable at a time (OVAT) experiments, which vary only one factor or variable at a time while keeping others fixed. However, statistically designed experiments that vary several factors simultaneously are more efficient when studying two or more factors as mentioned in chapter II. This chapter describes experimental design technique and response surface methodology that applied as a tool for this research.

3.1 Experimental design principal

Experimental design or design of experiments (DOE) is a statistical technique that consists of purposeful changes of the inputs (factors) to a process (or activity) in order to observe the changes in the output (responses). This allows obtaining the maximum information of a given process at a minimum procedure.

It requires less resource (experiments, time, material, etc.) for the amount of information obtained. This can be of major importance in industry, where experiments can be very expensive and time consuming. The estimates of the effects of each factor are more precise. Using more observations in order to estimate an effect results in higher precision (reduced variability) For example, for full and fractional factorial designs, all the observations are used to estimate the effect of each factor and each interaction (property of hidden replication), while typically only two of the observations in an OVAT experiment are used to estimate the effect of each factor.

The interaction between factors can be estimated systematically. Interactions are not able to estimate by OVAT experiments. Engineers who are not using this technique may miss this significant.

There is experimental information in a larger region of the factor space. This improves the prediction of the response in the factor space by reducing the variability of the estimates of the response in the factor space, and makes process optimization more efficient because the optimal solution is searched for over the entire factor space

Experimental designs can be summarized as:

1) the most effective method for identifying the key input factors

2) the most efficient way to gain an understanding of the relationship between the input factors and the response

3) a method for building a mathematical model relating the response to the input factors, which is often referred to as process/product characterization

4) a means of determining the settings of the input factors which optimize the response and minimize cost

5) a scientific method for setting tolerances

And obtaining good results from DOE involves these seven steps:

1) Set objectives

2) Select process variables

3) Select an experimental design

4) Execute the design

5) Check that the data are consistent with the experimental assumptions

6) Analyze and interpret the results

7) Use/present the results (may lead to further runs or DOE's).

3.2 Application of Experimental design for this research

Types of experimental design depend on objective of the experiment. Experimental designs are applied with this research for two objectives. First is screening purpose. The objective of this design is to screen the variables which have high effect on the result. Theses high effect variables will be selected to study in more detail about the irresponses to the result. The second purpose will be achieved by doing other type of experimental design such as response surface design which allows

us to estimate the interaction and even quadratic effect, and therefore give us an idea of the (local) shape of the response surface we are investigating.

3.2.1 Screening objective

For this research, Plackett-Burman designs (well known as screening design and has been tested by many successful approaches) are chosen experimental designs for its usefulness in screening a relative large number of factors with a minimum of number of simulation.

In 1946, Robin L. Plackett and J. P. Burman published their now famous paper "The Design of Optimal Multifactorial Experiments" in Biometrika (vol.33). This paper describes the construction of very economical designs with the run number a multiple of four (rather than a power of 2).

Their goal was to find experimental designs for investigating the dependence of some measured quantity on a number of independent variables (factors), each taking L levels, in such a way as to minimize the variance of the estimates of these dependencies using a limited number of experiments.

Interactions between the factors were considered negligible. The solution to this problem was to find an experimental design in which each combination of levels for any pair of factors appears the same number of times. A complete factorial design would satisfy this criterion, but the idea was to find smaller designs.

For the case of two levels (L=2), Plackett and Burman used the method found in 1933 by Raymond Paley for generating orthogonal matrices whose elements are all either 1 or -1 (Hadamard matrices). Paley's method could be used to find such matrices of size N for most N equal to 4 times an integer. In particular, it worked for all such N up to 100 except N=92. If one is trying to estimate less than N parameters (including the overall average) then one simply uses a subset of the columns of the matrix.

Table 3.1 shows an example of series of input, generated by Plackett-Burman design, which used for an experiment containing 11 factors.

Table 3.1 Plackett-Burman Design in 12 Runs for up to 11 Factors

	Pattern	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
1	+ + + + + + + + + + +	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1
2	- + - + + + - - - + -	-1	+1	-1	+1	+1	+1	-1	-1	-1	+1	-1
3	- - + - + + + - - - +	-1	-1	+1	-1	+1	+1	+1	-1	-1	-1	+1
4	+ - - + - + + + - - -	+1	-1	-1	+1	-1	+1	+1	+1	-1	-1	-1
5	- + - - + - + + + - -	-1	+1	-1	-1	+1	-1	+1	+1	+1	-1	-1
6	- - + - - + - + + + -	-1	-1	+1	-1	-1	+1	-1	+1	+1	+1	-1
7	- - - + - - + - + + +	-1	-1	-1	+1	-1	-1	+1	-1	+1	+1	+1
8	+ - - - + - - + - + +	+1	-1	-1	-1	+1	-1	-1	+1	-1	+1	+1
9	+ + - - - + - - + - +	+1	+1	-1	-1	-1	+1	-1	-1	+1	-1	+1
10	+ + + - - - + - - + -	+1	+1	+1	-1	-1	-1	+1	-1	-1	+1	-1
11	- + + + - - - + - - +	-1	+1	+1	+1	-1	-1	-1	+1	-1	-1	+1
12	+ - + + + - - - + - -	+1	-1	+1	+1	+1	-1	-1	-1	+1	-1	-1

After using Plackett-Burman designs to generate the series of experiments and output was obtained, Pareto chart is a tool that ordering the effects of each parameter to the result by focus on their main effects. This tool helps researcher to compare the effects of each input variables easily.
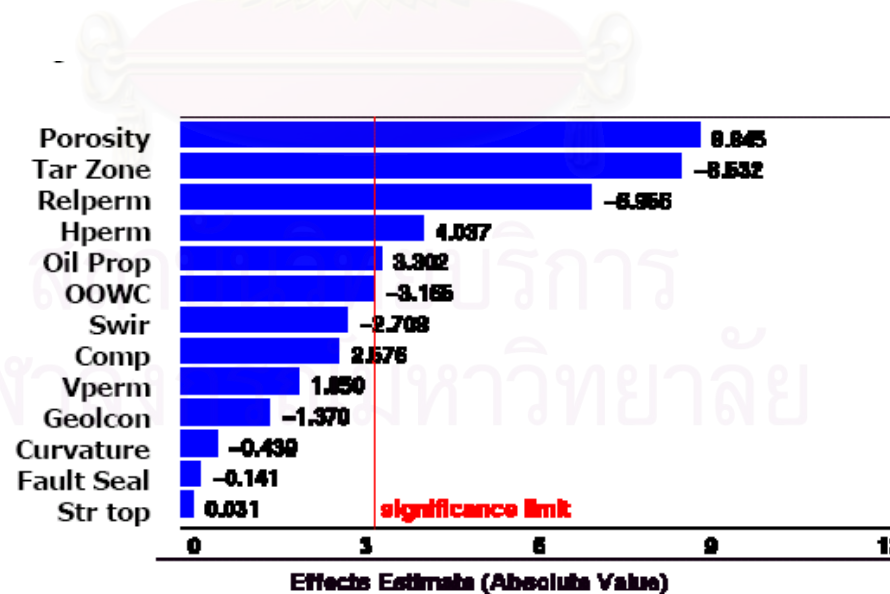
Figure 3.1 Examples of Pareto chart for oil and gas simulation approach

Figure 3.1 shows an example of Pareto chart applied for uncertainties assessment in waterflood project in Minagish Oolite reservoir which done by Peake[4]. As we can see from the figure, porosity has the highest main effect to the results ordered to the top of vertical axis, follow by other input variables which has lower effects subsequently. By setting up cut off value, a group of high effect variables were selected to the next step to study in more detail about its response to the results.

3.2.2 Response surface objective

To capture the significant quadratic effects for prediction purposes or to increase the design runs to accommodate more potential effects, a 2-levels design matrix must add with extra design runs, such as two extremes and the base case. Because 2-level design can capture only linear result and cannot capture the curvature of the result as describe in figure 3.2
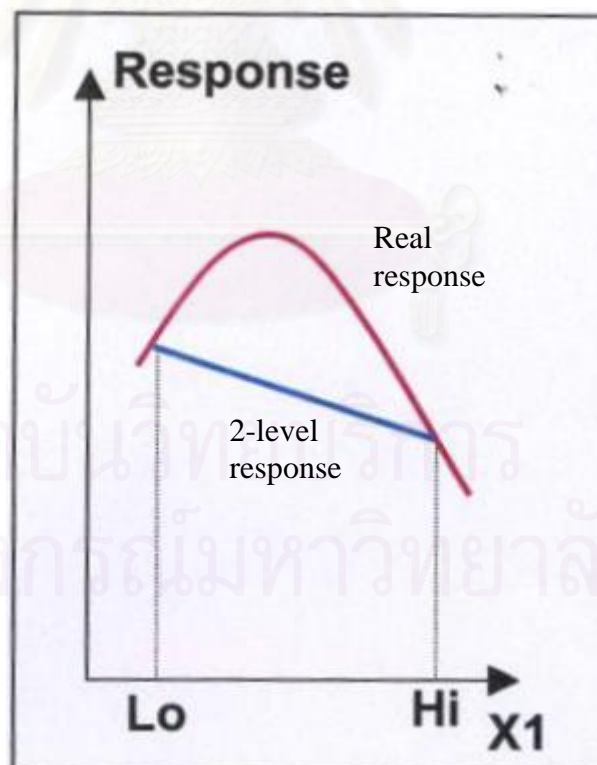
Figure 3.2 Limitation of 2-level design

So the experimental design in this section will be commonly done by 3-level of the input value that allows us to capture the curvature of the result. Next part

describes Central Composite Design which used for response surface approach for this research.

a) Central Composite Designs (CCD)

A Box-Wilson Central Composite Design, commonly called `a central composite design,' contains an imbedded factorial or fractional factorial design with center points that is augmented with a group of `star points' that allow estimation of curvature. If the distance from the center of the design space to a factorial point is ± 1 unit for each factor, the distance from the center of the design space to a star point is $\pm \alpha$ with $|\alpha| > 1$. The precise value of α depends on certain properties desired for the design and on the number of factors involved. A central composite design always contains twice as many star points as there are factors in the design.

Similarly, the number of center-point runs that the design should contain also depend on certain properties required for the design.
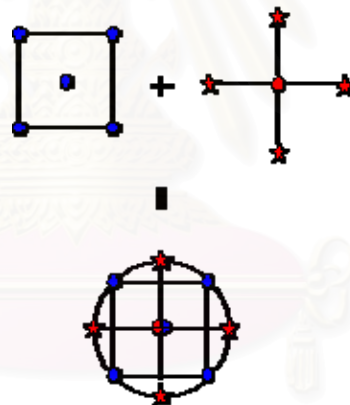
Figure 3.3: Generation of a central composite design for two factors

A central composite design always contains twice as many star points as there are factors in the design. The star points represent new extreme values (low and high) for each factor in the design. Table 3.2 summarizes the properties of the three varieties of central composite designs.

Table 3.2: Central Composite Design

Central Composite Design Type	Terminology	Comments
Circumscribed	CCC	CCC designs are the original form of the central composite design. The star points are at some distance α from the center based on the properties desired for the design and the number of factors in the design. The star points establish new extremes for the low and high settings for all factors. Figure 3.4 illustrates a CCC design. These designs have circular, spherical, or hyperspherical symmetry and require 5 levels for each factor. Augmenting an existing factorial or resolution V fractional factorial design with star points can produce this design.
Inscribed	CCI	For those situations in which the limits specified for factor settings are truly limits, the CCI design uses the factor settings as the star points and creates a factorial or fractional factorial design within those limits (in other words, a CCI design is a scaled down CCC design with each factor level of the CCC design divided by α to generate the CCI design). This design also requires 5 levels of each factor.
Face Centered	CCF	In this design the star points are at the center of each face of the factorial space, so $\alpha = \pm 1$. This variety requires 3 levels of each factor. Augmenting an existing factorial or resolution V design with appropriate star points can also produce this design.
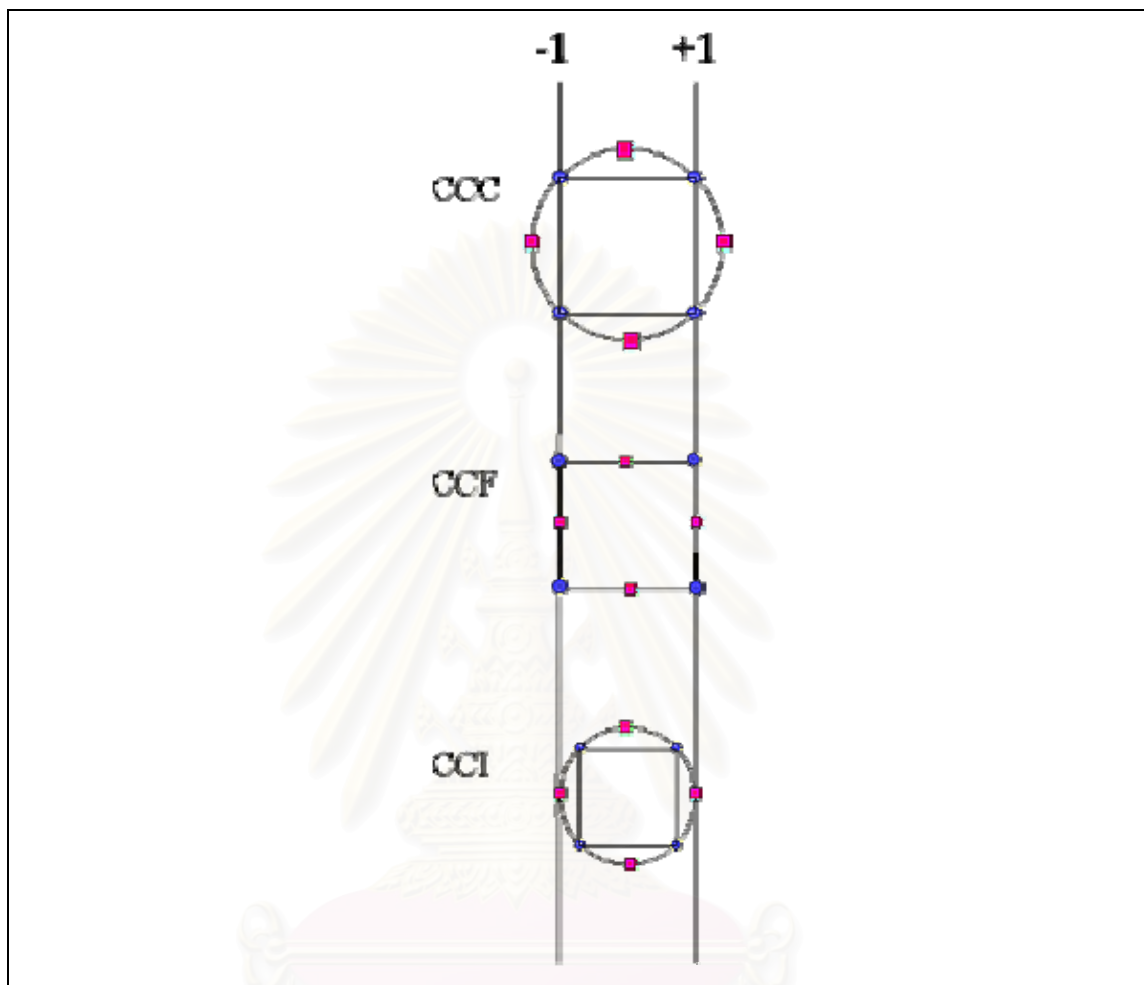
Figure 3.4: Comparison of the Three Types of Central Composite Designs

The diagrams in figure 3.4 illustrate the three types of central composite designs for two factors. Note that the CCC explores the largest process space and the CCI explores the smallest process space. Both the CCC and CCI are rotatable designs, but the CCF is not. In the CCC design, the design points describe a circle circumscribed about the factorial square. For three factors, the CCC design points describe a sphere around the factorial cube.

b) Determining α in Central Composite Designs

To maintain rotatability, the value of α depends on the number of experimental runs in the factorial portion of the central composite design:

α = [number of factorial runs]$^{1/4}$

If the factorial is a full factorial, then

$$\alpha = \left[2^k\right]^{1/4} \tag{3.1}$$

However, the factorial portion can also be a fractional factorial design of resolution V (Variance). Table 3.3 illustrates some typical values of α as a function of the number of factors.

Table 3.3: Determining for rotatability.

Number of Factors	Factorial Portion	Scaled Value for Relative to ±1
2	2	$2^{2/4} = 1.414$
3	2^3	$2^{3/4} = 1.682$
4	2^4	$2^{4/4} = 2.000$
5	2^{5-1}	$2^{4/4} = 2.000$
5	2^5	$2^{5/4} = 2.378$
6	2^{6-1}	$2^{5/4} = 2.378$
6	2^6	$2^{6/4} = 2.828$

The value of α also depends on whether or not the design is orthogonally blocked. That is, the question is whether or not the design is divided into blocks such that the block effects do not affect the estimates of the coefficients in the 2nd order model.

3.3 Response surface methodology (RSM)

Response surface methodology (RSM) explores the relationship between several explanatory variables and one or more response variables. The method was introduced by G. E. P. Box and K. B. Wilson in 1951. The main idea of RSM is to use a set of designed experiments to obtain an optimal response.

A response surface, also called surrogate model or a proxy is a representation of a real system or its simulation.
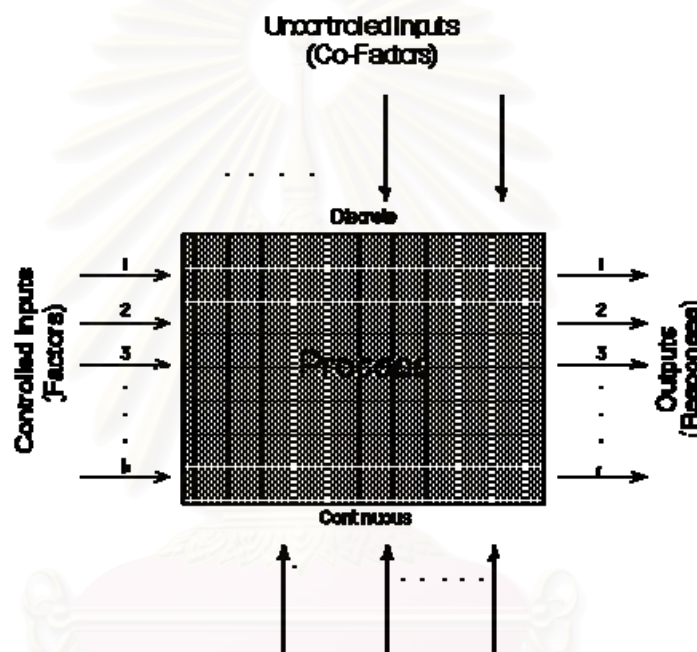
Figure 3.5: Process Model Schematic

Consider a system (Figure 3.5), whose output response variable y is a function of multiple input parameters x_i, i=1,2,…,n

$$y = f(x_1, x_2, ..., x_n) + \varepsilon \qquad (3.2)$$

Here, ε represents the random error, which has an independent normal distribution with zero expectation and uniform variance. The expect value $E(y) = f(x_1, x_2, ..., x_n)$ is called a response surface (RS). Constructing responses should meet two requirements:

1. RS must accurately represent the output response variable y.
2. Computational efficiency must be optimized.

Response surface is usually constructed with regression method, interpolation method and neural network. The most common empirical models fit to the experimental data take either a *linear* form or *quadratic* form.

A *linear model* with two factors, X_1 and X_2, can be written as

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 + \text{experimental error} \tag{3.3}$$

Here, Y is the response for given levels of the main effects X_1 and X_2 and the $X_1 X_2$ term is included to account for a possible interaction effect between X_1 and X_2. The constant β_0 is the response of Y when both main effects are 0.

For a more complicated example, a linear model with three factors X_1, X_2, X_3 and one response, Y, would look like (if all possible terms were included in the model)

$$
\begin{aligned}
Y = {} & \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_{12} X_1 X_2 \\
& + \beta_{13} X_1 X_3 + \beta_{23} X_2 X_3 + \beta_{123} X_1 X_2 X_3 \\
& + \text{experimental error}
\end{aligned}
\tag{3.4}
$$

A *second-order* (quadratic) model (typically used in response surface DOE's with suspected curvature) does not include the three-way interaction term but adds three more terms to the linear model, namely

$$\beta_{11} X_1^2 + \beta_{22} X_2^2 + \beta_{33} X_3^2. \tag{3.5}$$

Figures 3.6 through 3.8 illustrate possible behaviors of responses as functions of factor settings. In each case, assume the value of the response increases from the bottom of the figure to the top and that the factor settings increase from left to right.

Figure 3.6: Linear function
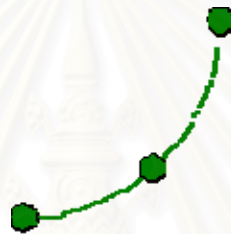
Figure 3.7: Quadratic function

Figure 3.8: Cubic function

Some extensions of response surface methodology deal with the multiple response problem. Multiple response variables create difficulty because what is optimal for one response may not be very optimal for other responses. Other extensions are used to reduce variability in a single response while targeting a specific value, or attaining a near maximum or minimum while preventing variability in that response from getting too large.

Significant criticisms of RSM include the fact that the optimization is almost always done with a model for which the coefficients are estimated, not known. That is, an optimum value may only look optimal, but be far from the truth because of

variability in the coefficients. A contour plot (figure 3.9) is frequently used to find the responses of two variables to find these coefficients by including a large number of trials in each and combinations of them, and using some sort of interpolation to find potentially better intermediate values between them.
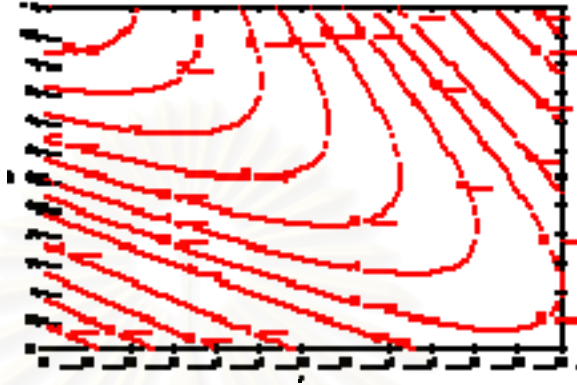
Figure 3.9: An example of contour plot for response assessment

But since experimental runs often cost a lot of time and money, it can also be difficult to pinpoint the ideal coefficients, as well; there are frequently strategies used to find those values with minimal runs. Experimental designs used in RSM must make tradeoffs between reducing variability and reducing the negative impact that can be caused by bias.

CHAPTER IV

INTEGRATED PRODUCTION MODELING TOOLKITS

This chapter introduces function of the application named "Integrated Production Modeling Toolkits" which is selected for the research.

Petroleum Experts have developed the integrated production modeling toolkits (IPM) which models the complete production system from the reservoir to the surface network.

Integrating the tools of GAP, PROSPER, MBAL, REVEAL, PVTP and OPENSERVER to operate seamlessly, the engineer is able to design complex field models. The reservoir, wells and complete surface systems model, having been matched for production history, will accurately optimize the entire network and run predictions.

GAP, PROSPER and MBAL are main parts of the simulation and was selected to build simulation model for this research. Being used OPENSERVER to transfer data to simulation model in order to decrease error due to manual input.

4.1 MBAL

MBAL is in a package made up of various tools designed to gain a better understanding of the reservoir behavior and perform prediction run. Some of the tools are material balance, reservoir allocation, decline curve analysis, Monte Carlo volumetric and multilayer. And material balance tool was selected to build reservoir model which is one part of simulation model.

The material balance is well known as basic tool of reservoir engineers for interpreting and predicting reservoir performance. The general material balance

equation was first developed by Schilthuis in 1936. Since that time, the use of the computer and sophisticated multidimensional mathematical models has replaced the zero dimensional Schilthuis equation in many applications. However, the Schilthuis equation, if fully understood, can provide great insight for the practicing reservoir engineer. Following the discussion of the gas material balance equation is presented.

4.1.1 Gas material balance equations

Material-balance equations equate the volume of a mass of material at a particular pressure and temperature to the volume of the same mass of material at some different pressure and temperature. In a petroleum reservoir, including a gas reservoir, we define the original free-gas volume in the reservoir as G and state this volume in standard cubic feet. Thus, the original reservoir volume of free gas in barrels is the product of G and the initial gas formation volume factor, B_{gi}, stated in reservoir volume per standard cubic feet. If the gas reservoir is not subjected to a water drive and no interstitial water is produced, the reservoir volume occupied by the gas normally remains constant for all practical purposes. Thus, the same initial reservoir volume can be stated in terms of the gas remaining in the reservoir at any particular time after some standard cubic feet of gas, G_p, has been produced.

At this time the volume of gas remaining in the reservoir is $\left(G - G_p\right)$ in standard cubic feet, and the reservoir volume is $\left(G - G_p\right)B_g$ in reservoir condition when the gas volume is converted to the current reservoir pressure. Therefore, the gas formation volume factor used to make this conversion must be based on the average reservoir pressure that exists after G_p standard cubic feet of gas has been produced. We can then equate the reservoir gas volume stated in these two different ways to obtain the material-balance equation for a gas reservoir that does not have a water drive and where no interstitial water is produced:

$$GB_{gi} = \left(G - G_p\right)B_g \qquad (4.1)$$

If a gas reservoir is subjected to a water drive, the gas volume in the reservoir is reduced as the water encroaches into the original gas-bearing portion of the reservoir. The volume of gas in the reservoir initially, GB_{gi}, less the volume of gas in the reservoir at some time after a volume of gas, G_p, has been produced, $(G - G_p)B_g$, is equal to the volume of water that has entered the original gas-bearing pores of the reservoir if none of the encroached water has been produced. If W_p barrels of the encroached water have been produced, the difference is equal to the total number of barrels of water that have encroached into the original gas-bearing portion of the reservoir W_e. Water isothermal compressibility c_w and Formation isothermal compressibility c_f also included in the calculation in order to account with initial water expansion and changing in rock volume respectively. Then the general gas material balance equation can be expressed as:

$$G\left(B_g - B_{gi}\right) + GB_{gi}\left[\frac{c_w S_{wi} + c_f}{1 - S_{wi}}\right]\Delta\overline{p} + W_e = G_p B_g + B_w W_p \quad (4.2)$$

The original gas in place can be calculated volumetrically, and the water encroachment can be using aquifer model which presented in the next part.

4.1.2 Aquifer models

MBAL provided aquifer models for linear, radial and bottom drive that developed by many author including

- Small pot
- Schithuis Steady State
- Hurst Simplified
- Hurst and van Everdingen
- Vogt and Wang
- Fetkovich Semi Steady State

- Fetkovich Steady State
- Carter – Tracy
- Multi Tank

These aquifer models can be selected to associate with material balance calculation in MBAL. Hurst van Everdingen model is a selected model for this research. Because, input parameters required for this model such as reservoir thickness, reservoir radius and encroachment angle are available with existing data. And this model has been proved to work efficiently in many case of study in the Gulf of Thailand.

4.1.3 Relative permeability

Relative permeability is required for production prediction. MBAL using Corey Functions as a format for input data. The required parameters are

- Residual saturation

These saturations are used to calculate the amount of oil or gas by-passed during a gas or water flooding.

- End points

Define maximum saturation for each phase of its relative permeability. For example, for the oil, it corresponds to its relative permeability at So = (1-Swc)

- Corey exponents

Define the shape of the relative permeability curve between zero and the end point. A value of 1.0 will give a straight line. A value less than one will give a shape with curve above straight line. A value greater than one will give a shape with curve below straight line.

In a Corey function, the relative permeability for the phase x is expressed as

$$K_{rx} = E_x \left(\frac{S_x - S_{rx}}{S_{mx} - S_{rx}} \right)^{nx} \qquad (4.14)$$

where

E_x is the end point for the phase x

nx is the Corey exponent

S_x is the phase saturation

S_{rx} is the phase residual saturation and

S_{mx} is the phase maximum saturation

The phase absolute permeability can then be expressed as :

$$K_x = K * K_{rx} \tag{4.15}$$

where

K is the reservoir absolute permeability

K_{rx} is the relative permeability of phase x

4.2 PROSPER

PROSPER is a fundamental element in the Integrated Production Model (IPM) mainly used for all the calculations in the well section. Its PVT section also can generate fluid properties using standard correlations and allows them to be modified to better fit measured lab data.

The tool can be used to model reservoir inflow performance (IPR) for single, multilayer, or multilateral wells with complex and highly deviated completions, optimizing all aspects of a completion design including perforation details and gravel packing. The following table lists the inflow performance options:

Table 4.1: inflow performance options available in PROSPER

IPR Method	Oil & Water	Dry & Wet Gas	Retrograde Condensate
Back Pressure		✓	✓
C and n		✓	✓
Composite	✓		
Darcy	✓		
Dual Porosity	✓	✓	✓
External Entry	✓	✓	✓
Fetkovich	✓		
Forchheimer		✓	✓
Forchheimer with Pseudo - Pressure NEW!!!		✓	✓
Multirate Forchheimer with Pseudo - Pressure NEW!!!		✓	✓
Horizontal well - No Flow Boundaries	✓	✓	✓
Horizontal well - Constant Pressure upper boundary	✓		
Horizontal well - dP friction	✓	✓	✓
Horizontal well - transverse vertical fractures	✓	✓	✓
Hydraulically fractured	✓	✓	✓
Jones	✓	✓	✓
Multi-lateral	✓	✓	✓
Multi-layer	✓	✓	✓
Multi-layer - dP Loss	✓	✓	✓
Multi-rate C and n		✓	✓
Multi-rate Fetkovich	✓		
Multi-rate Jones	✓	✓	✓
Modified Isochronal IPR		✓	✓
Petroleum Experts		✓	✓

Because of this research focus on gas field and availability of IPR input, Jones method was selected in order to construct IPR for simulator and network model.

The Jones equation for gas is modified form of Darcy equation, which allows for both laminar and non-Darcy flow pressure drops. The Jones equation can be expressed in the form:

$$P_R^2 - P_{wf}^2 = aQ^2 + bQ \qquad (4.16)$$

Where "a" and "b" are calculated from reservoir properties or can be determined from multi-rate test. Required data entry is:

- Reservoir permeability (Total permeability)
- Formation thickness (Thickness of producing reservoir rock)
- Drainage area
- Wellbore radius
- Dietz shape factor (depend on the shape of drainage area)

Another important part of PROSPER is generating tubing lift curves for use in reservoir and total system simulator. It provide pressure drop in wellbore and pressure loss in the surface gathering system calculation.

The pressure loss in a pipeline or wellbore is the summation of 3 components:

- Gravity Head
- Friction loss
- Acceleration

where,

$$\Delta p_{total} = \Delta p_{gravity} + \Delta p_{friction} + \Delta p_{acceleration} \qquad (4.19)$$

The gravity component is due to the density of the fluid mixture at each point in the system and is a complex function of the relative velocity of the phase present. PROSPER makes a flash computation at each calculation step to determine the proportion s of each phase and the predicted density at each pressure and temperature step.

Industry standard 2-phase calculations are then applied to determine the increase in apparent fluid density due to the higher vertical velocity of gas compared to oil and water (slippage). The gravity head loss is proportional to the fluid density corrected for slip. The slip correction to be applied depends on the flow regime, fluid velocity etc. the need for an accurate PVT description for predicting the gravity head loss is clear.

Friction losses are controlled by fluid viscosity and geometric factors (pipe diameter and roughness). In the majority of oilfield application, (i.e. large elevation difference between inlet and outlet with liquids present) the gravitational component normally accounts for around 90% of the overall head loss. Therefore, the total pressure drop function is not particularly sensitive to the value of the friction loss coefficient.

The acceleration component is usually small except in the systems involving significant fluid expansion. However, it is accounted for in all PROSPER calculations.

Vertical lift correlations available in PROSPER are

- Duns and Ros (Modified for condensates)

- Duns and Ros Original

- Hagedorn-Brown

- Fancher-Brown

- Gray

- Orkiszewski

- Petroleum Experts

- Petroleum Experts 2

- Petroleum Experts 3 (bio-degraded oils)

- GRE (Modified by PE)

- Petroleum Experts 4 (Advance mechanistic model for angled wells)

- OLGAS – Olga 2-phase and Olga 3-phase correlations.

The selected vertical lift correlation for this research is Petroleum Experts 2. This model has been recommended by Petroleum Expert company that it is suitable with reservoir condition and fluid properties in the Gulf of Thailand.

Figure 4.1 shows example plot of VLP curves which is calculated by PROSPER
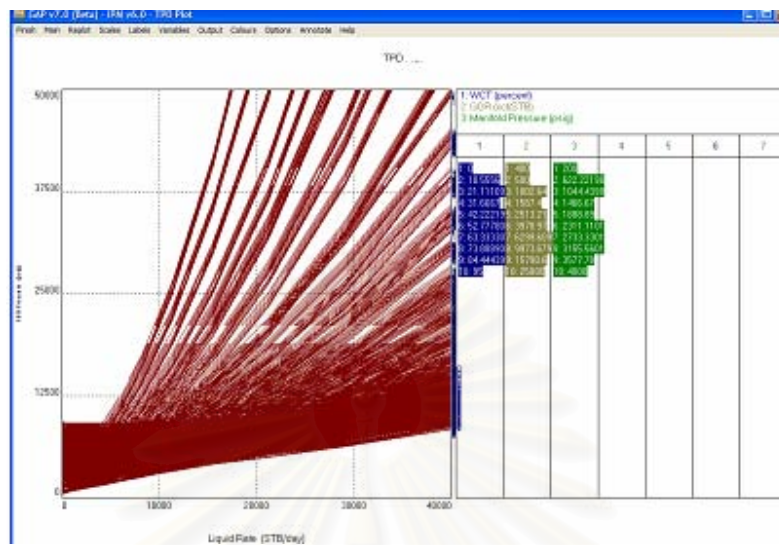
Figure 4.1: VLP generated by Prosper

Integrating IPR and VLP which is calculated by PROSPER is an important part of GAP input, which is describe later, in order to run the production forecast.

4.3 GAP

General Allocation Package (GAP) is a multiphase optimizer of the surface network which link with PROSPER and MBAL to model reservoir and production system. GAP allows engineer to build complete system models, including the reservoirs, well such as naturally flowing oil wells, gas-lifted wells, ESP operated wells etc. and surface system.
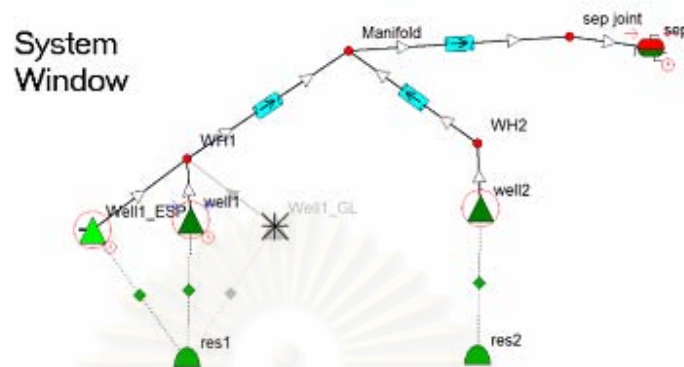
Figure 4.2: Network model construct by GAP

The optimizer controls production rates using wellhead chokes to maximize the hydrocarbon production while honoring constraints at the gathering system, well and reservoir levels. GAP models both production and injection systems simultaneously, containing gas, condensate and/or water wells to generate production profiles.

GAP prediction calculates optimized production over user-defined time steps. Tank pressure decline curve or MBAL material balance models can be used to provide reservoir pressures and saturations. GAP automatically re-calculates well IPR for the current reservoir conditions (and re-calculates the well performance curves if the user is using performance curve option), then performs the network solver to find the well production rates.

Using the well rates, cumulative production for each well and reservoir tank is calculated. The reservoir model (decline curve or MBAL material balance) is used to find the reservoir pressure at the end of each time step. The entire process is repeated stepwise until the end of the prediction time reached.

Each well connected to a tank shares the same reservoir pressure. The parameter IPR Offset dP is optionally used to shift the reservoir pressure from the tank datum to each well's intake node depth.

Reservoir targets can be set for each tank and abandonment limits for each well. GAP will calculate how much water or gas inject is required to maintain tank pressure within the user-specified end of prediction target pressure. Well, tank, separator and joint constraints can be scheduled in time and the results plotted.

4.4 OPENSERVER

OPENSERVER is designed to provide an open architecture for all the Petroleum Experts products. This will allow the programs to be directly accessed and be driven by other third party programs.
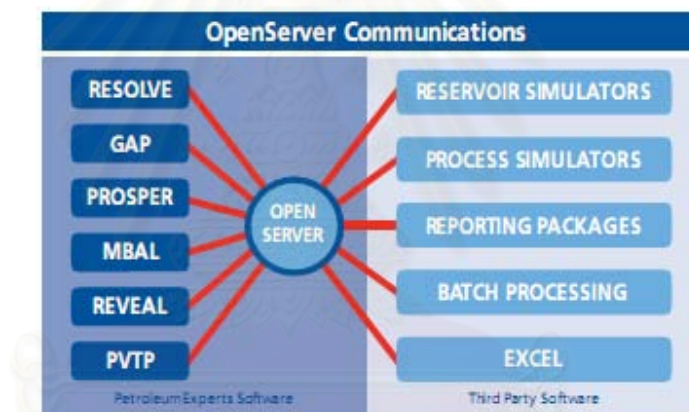
Figure 4.3: OpenServer communications

The OPENSERVER can be used for transferring data between databases such as MS Excel or programs written in Visual Basic and PETEX programs or can be used for automated procedure in order to eliminate manual steps.

CHAPTER V

METHODOLOGY AND RESULT

This chapter is separated into four parts. First part is to introduce "P Field" which will be used as reference field, also data obtaining to develop simulation model. Second part is to build surrogate model, Experimental design technique generates series of input to simulate series of output covering result range. Regression analysis was applied to develop surrogate model. Third part is quality of surrogate model testing. Fourth part describes how to apply the surrogate model to forecast field production.

5.1 "P Field" Overview

The P Field is located in the southern part of the Gulf of Thailand. Production from "P Field", mainly gas and condensate, began its first production in 1990s

"P Field" located in the southern most of Pattani basin and contains several structurally complex trans-tensional basins. These are made up of asymmetrical grabens filled with non-marine to marginal marine Tertiary sediments as old as Eocene. Underlying the graben sediments are a variety of Paleozoic marine carbonates, granitic intrusive rocks, and metasediments. The limited lateral extent of these deposits, combined with vatiations in heat flow and depth of burial of the source rocks, causes the distribution of hydrocarbons to be complex and difficult to predict.

Figure 5.1 shows multi-layered commingled gas reservoir which commonly found in this field. Each reservoir has different reservoir properties and fluid properties. This creates complexity in operation.
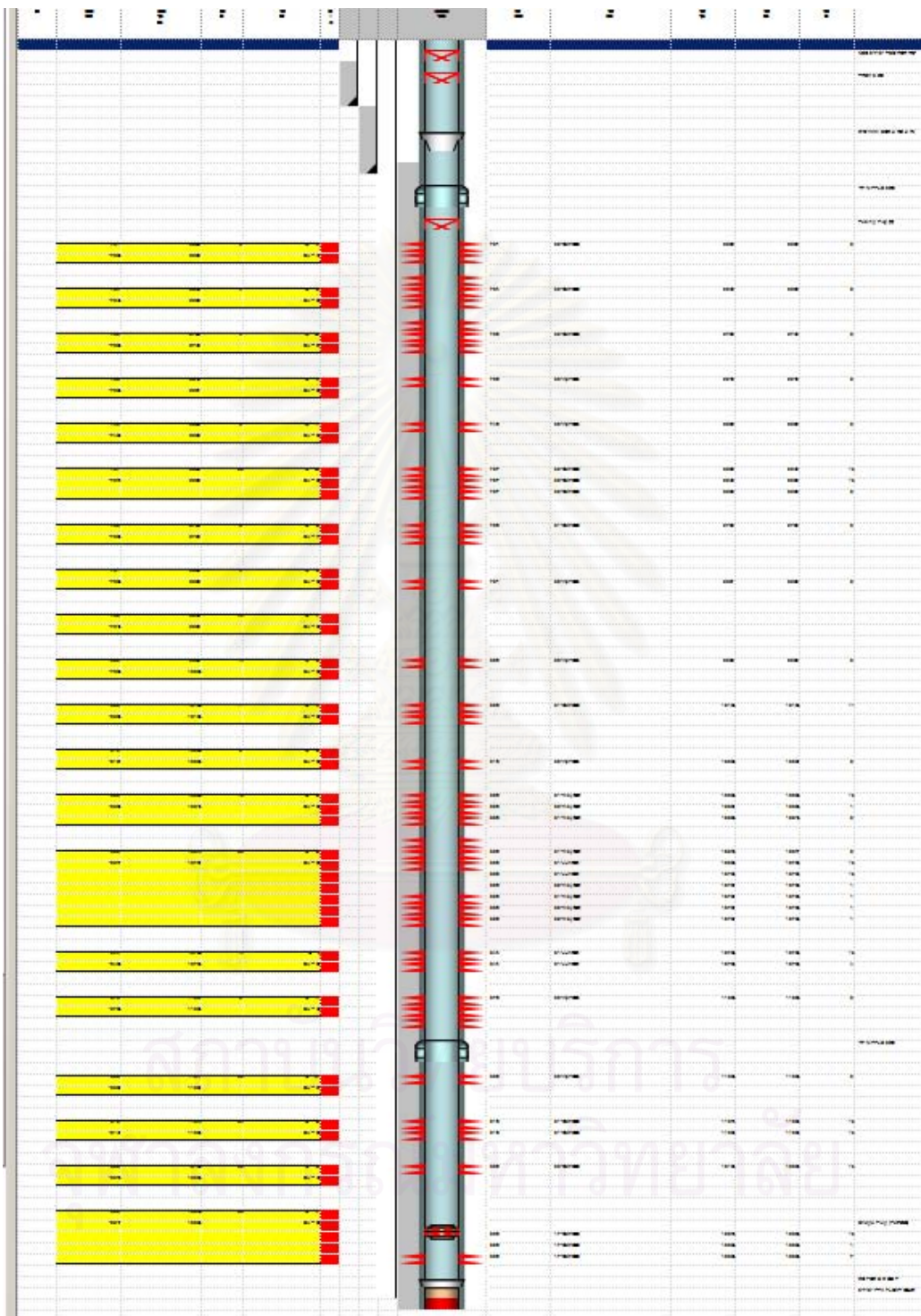
Figure 5.1: Typical well schematic

5.1.1 "P Field" correlations

The number of input variables for doing experimental design and response surface will affect the number of simulation run and might be difficult for generating response surface. If there is a correlation between input variables, we can select only one variable to generate the input to the process and input correlated variables by its calculated value. This can help us to decrease the number of input variables.

In this section, some of correlations in data which found in the previous study were introduced.

a) Subsurface depth – Temperature correlation

The increasing of temperature with depth was studied for "P Field". Figure 5.2 shows sample data which obtained from field and plotted with depth in order to find the correlation between these two parameters.

The correlation obtained is

$$\boxed{T\left(^\circ F\right)=115.23-0.0283\times TVDSS} \tag{5.1}$$

Where;

T   is temperature (F°)

TVDSS is true vertical depth subsea (ft)
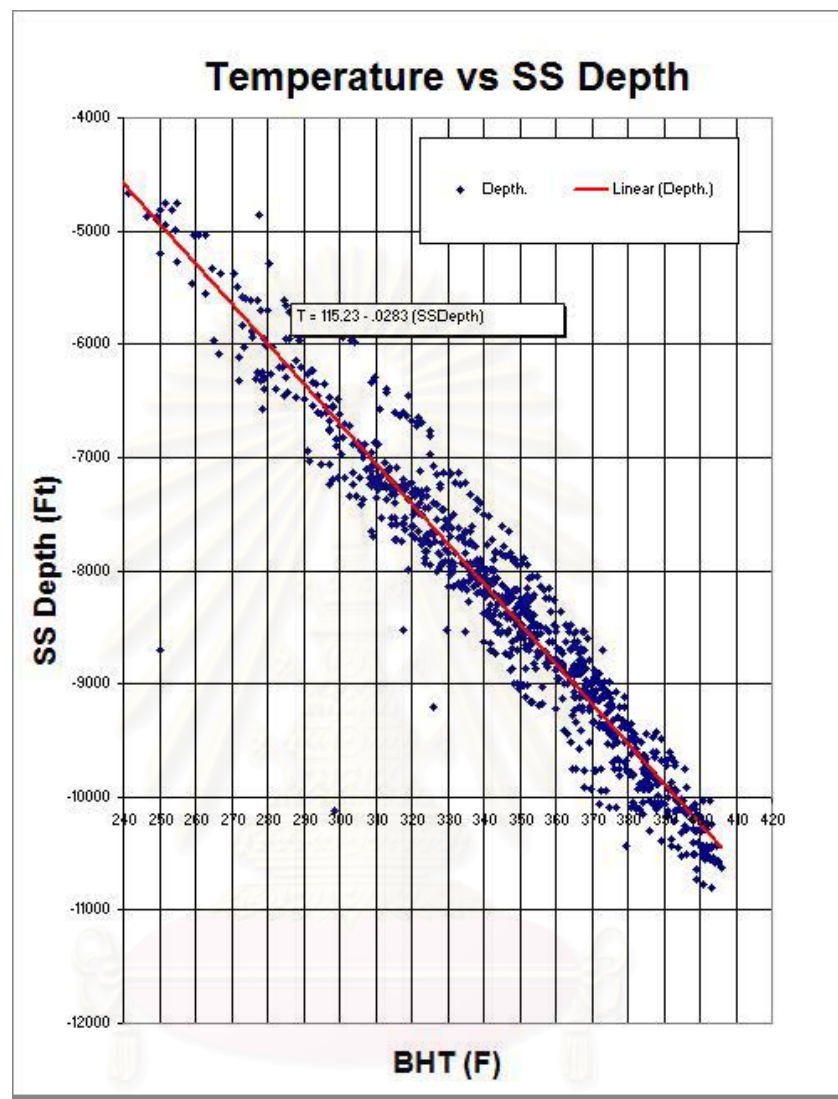
Figure 5.2: Temperature VS Subsea depth

b) Permeability - Log Porosity correlation

The correlation between porosity and permeability was also obtained from the previous study. This equation can be expressed as:

$$k = 0.0048e^{44.843\phi} \tag{5.2}$$

where;

        k   is permeability (md)

        Ø   is porosity (%)

5.1.2 "P Field" parameters statistics

Statistics of reservoir and fluid properties obtained from field are summarized into table which consists of general reservoir properties and characteristics, well characteristics, surface facilities and other necessary data to construct reservoir model. These values will be used as input for experimental design process in the next part.

Table 5.1: "P Field" statistic

Parameters		P10	P50	P90
Gas gravity		0.96478	0.9989	1.0684
CGR	*(bbl/MMscf)*	36.67	52.86	85.90
Condensate gravity	*(API)*	41.54	48.6	57.2
Reservoir Pressure Gradient	*(ppg)*	7.75	8.93	10.463
Porosity	*(fraction)*	0.132	0.155	0.184
Pay Thickness	*(ft)*	29.2	64	117
MD/TVD	*(fraction)*	1.099	1.261	1.470
TVD	*(ft)*	-7785	-8525	-9096
Residual water	*(fraction)*	0.32	0.48	0.56
Total skin		-0.14	3	14.7
Flowline Pressure	*(psia)*	400	450	500

Where,

CGR is condensate gas ratio

TVD is true vertical depth of reservoir group

MD/TVD is the fraction of measured depth and true vertical depth of reservoir group. This parameter can identify deviation of well.

Table 5.2 summarizes averaged value of input parameters which have low effect to the production, such as kick off depth, and also including base case values for this research.

Table 5.2: "P Field" base case input

Parameters		
Kick off Depth	*(ft)*	1400
water salinity	*(ppm)*	30000
Mole% CO2	*(%)*	28.27
Mole % N2	*(%)*	2.52
Krw Endpoint		0.8
Water exponent		2
Residual gas	*(fraction)*	0.1
Krg Endpoint		0.8
Gas exponent		2
Reservoir radius	*(ft)*	1053
Outer/inner radius ratio	*(fraction)*	2.5
Encroachement angle	*(degree)*	180

Input parameters in this table can be separated into 3 groups. First group is low effect parameters including kick off depth of well, specify the position where well path starts to deviate from vertical, Water salinity and Gas impurities (CO_2 and N_2). Second group is relative parameter input parameters including Krw endpoint, water exponent, residual gas, Krg endpoint and Gas exponent. These parameters are required for Corey function calculation. Finally is the input for aquifer model including reservoir radius, outer/inner ratio (the ratio of aquifer radius and reservoir radius) and encroachment angle.

5.2 Surrogate model development

This research will focus on the production forecast technique by using experimental design and response surface method. Base on obtained data, normally it operates at stable surface condition by fix the chock size for each well as shown in figure 5.3. The base simulation model was constructed by IPM application in well level which contains stable surface condition that is constant choke size at 1 inch. The model was constructed by grouping reservoir in the same batch of perforation into one tank in the simulation model. The surrogate model developed by this simulation model is able to apply to the other wells that have similar surface condition too.
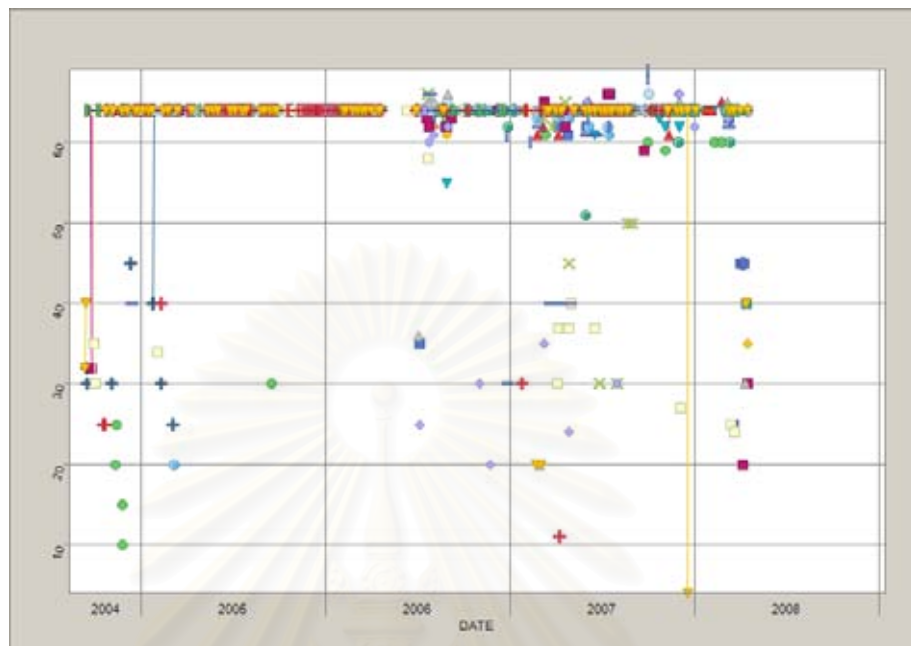
Figure 5.3: Operating Choke size

5.2.1 Simulation model construction

As discuss in the previous part, Integrated Production Modeling Toolkits software developed by Petroleum Expert was used to construct simulation model in well level for prediction the production. Figure 5.6 shows simulation model build in GAP.
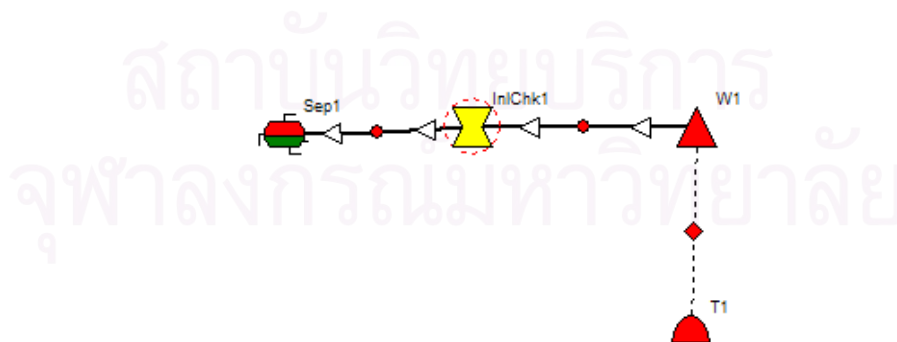
Figure 5.4: GAP simulation model

This symbol refers to separator. But the separator in GAP does not have to be the physical separator in the field. It is simply a point of fixed pressure in the network.

This symbol refers to choke.

This symbol refers to reservoir section which linkable to MBAL. All material balance calculation was completed here.

This symbol refers to well section which linkable to Prosper. The Inflow performance relationship and Vertical lift performance are calculated in this section.

5.2.2 Screening process

Initially a traditional method, one variable at a time (OVAT), was used to identify the high effect parameters. OVAT will change one input parameter to high and low value while keeping the other parameters constant at their average values. The value of input parameters for each case was summarized in table 5.3. a table of 22 different cases are required for 11 parameters.

The simulation model was run by using input parameter from table 5.3. The model simulated the production profile until reach the well production cutoff criteria at 0.5 MMscf/d.

Simulation output is not a single value of output for each case. But it is production profile which contains a series of production rate at each timestep. In this case, the parameters obtain from production profile that can capture production profile characteristic including Initial gas rate, Production period and Cumulative production at abandonment will be considered altogether in order to identify the high effect parameter.

Table 5.3: OVAT input parameters

Case	Gas gravity	CGR (bbl/MMscf)	Condensate gravity (API)	Reservoir Pressure Gradient (ppg)	porosity (fraction)	Pay Thickness (ft)	MD/TVD (fraction)	TVD (ft)	Residual water (fraction)	skin	Flowline Pressure (psia)
1	1.0684	52.86	48.6	8.93	0.155	64	1.261	-8524.5	0.478	3	450
2	0.96478	52.86	48.6	8.93	0.155	64	1.261	-8524.5	0.478	3	450
3	0.9989	85.90	48.6	8.93	0.155	64	1.261	-8524.5	0.478	3	450
4	0.9989	36.67	48.6	8.93	0.155	64	1.261	-8524.5	0.478	3	450
5	0.9989	52.86	57.2	8.93	0.155	64	1.261	-8524.5	0.478	3	450
6	0.9989	52.86	41.54	8.93	0.155	64	1.261	-8524.5	0.478	3	450
7	0.9989	52.86	48.6	10.463	0.155	64	1.261	-8524.5	0.478	3	450
8	0.9989	52.86	48.6	7.75	0.155	64	1.261	-8524.5	0.478	3	450
9	0.9989	52.86	48.6	8.93	0.184	64	1.261	-8524.5	0.478	3	450
10	0.9989	52.86	48.6	8.93	0.132	64	1.261	-8524.5	0.478	3	450
11	0.9989	52.86	48.6	8.93	0.155	117	1.261	-8524.5	0.478	3	450
12	0.9989	52.86	48.6	8.93	0.155	29.2	1.261	-8524.5	0.478	3	450
13	0.9989	52.86	48.6	8.93	0.155	64	1.470	-8524.5	0.478	3	450
14	0.9989	52.86	48.6	8.93	0.155	64	1.099	-8524.5	0.478	3	450
15	0.9989	52.86	48.6	8.93	0.155	64	1.261	-9096	0.478	3	450
16	0.9989	52.86	48.6	8.93	0.155	64	1.261	-7785	0.478	3	450
17	0.9989	52.86	48.6	8.93	0.155	64	1.261	-8524.5	0.56	3	450
18	0.9989	52.86	48.6	8.93	0.155	64	1.261	-8524.5	0.32	3	450
19	0.9989	52.86	48.6	8.93	0.155	64	1.261	-8524.5	0.478	14.7	450
20	0.9989	52.86	48.6	8.93	0.155	64	1.261	-8524.5	0.478	-0.14	450
21	0.9989	52.86	48.6	8.93	0.155	64	1.261	-8524.5	0.478	3	500
22	0.9989	52.86	48.6	8.93	0.155	64	1.261	-8524.5	0.478	3	400

Table5.4 summarizes result of OVAT for each case and then compares the differences between each parameter at high value and low value of input for each criteria.

Table 5.4: OVAT summary

Case	Parameter	Level	Result			Different in result between level		
			Initial Gas Rate (MMscf/d)	Production period (weeks)	Cumulative Gas production at abandonment (MMscf)	Initial Gas Rate (MMscf/d)	Production period (weeks)	Cumulative Gas production at abandonment (MMscf)
1	Gas gravity	High	8.892	57	1353	-0.026	2	38
2	Gas gravity	Low	9.076	55	1315			
3	CGR	High	8.341	59	1323	-0.145	5	-5
4	CGR	Low	9.357	54	1328			
5	Condensate gravity	High	9.04	56	1328	0.008	0	-2
6	Condensate gravity	Low	8.984	56	1330			
7	Reservoir Pressure gradient	High	10.748	55	1531	0.445	0	388
8	Reservoir Pressure gradient	Low	7.633	55	1143			
9	porosity	High	14.474	42	1626	1.404	-36	573
10	porosity	Low	4.643	78	1053			
11	Pay Thickness	High	12.031	79	2473	0.971	41	1895
12	Pay Thickness	Low	5.234	38	578			
13	MD/TVD	High	8.458	57	1315	0.044	-1	4
14	MD/TVD	Low	8.148	58	1311			
15	TVD	High	8.817	56	1351	0.131	-2	92
16	TVD	Low	7.903	58	1259			
17	Residual water	High	8.988	45	1112	0.000	-30	-606
18	Residual water	Low	8.988	75	1718			
19	skin	High	6.028	77	1271	-0.603	28	-74
20	skin	Low	10.247	49	1345			
21	Flowline Pressure	High	10.223	47	1321	0.173	-10	-26
22	Flowline Pressure	Low	9.013	57	1347			

The result from this table was plotted and ordering the effect into figure 5.5 to figure 5.7.
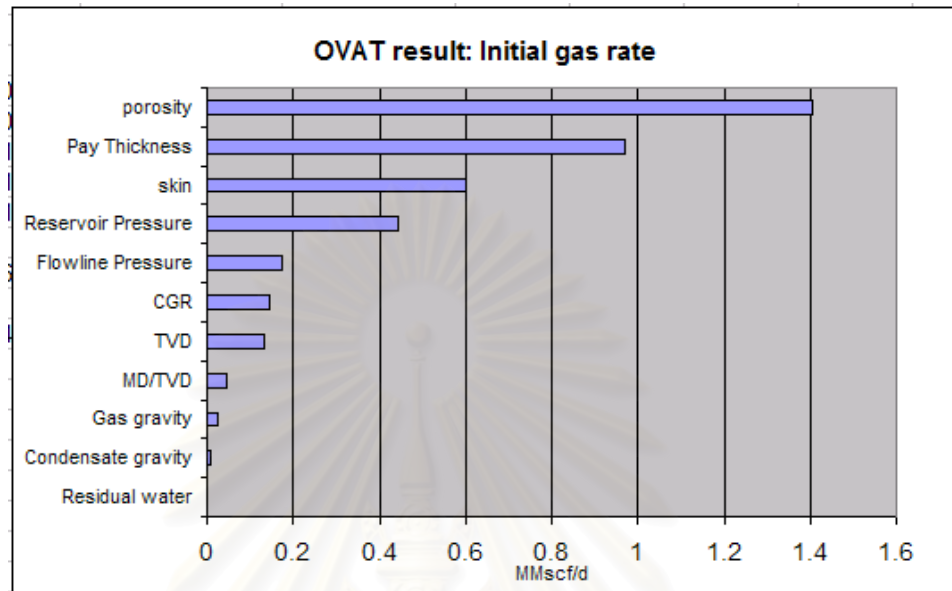
Figure 5.5: OVAT result – initial gas rate

As seen from figure 5.5 for initial gas rate criteria, main high effect parameters are porosity, pay thickness skin and reservoir pressure. Porosity was also used to calculate permeability value. This represents the ability of fluid flowing through rock. Higher porosity value will cause higher permeability value which means fluid can flow out from reservoir easier then gas rate will be higher. Higher pay thickness value also causes higher gas rate because this refers to area open to flow in wellbore. Reservoir pressure gradient and skin were considered in the part of pressure response. This gradient used for reservoir pressure calculation which refers to energy of reservoir and skin causes extra pressure loss around wellbore while flowing as a results of changing in gas rate.
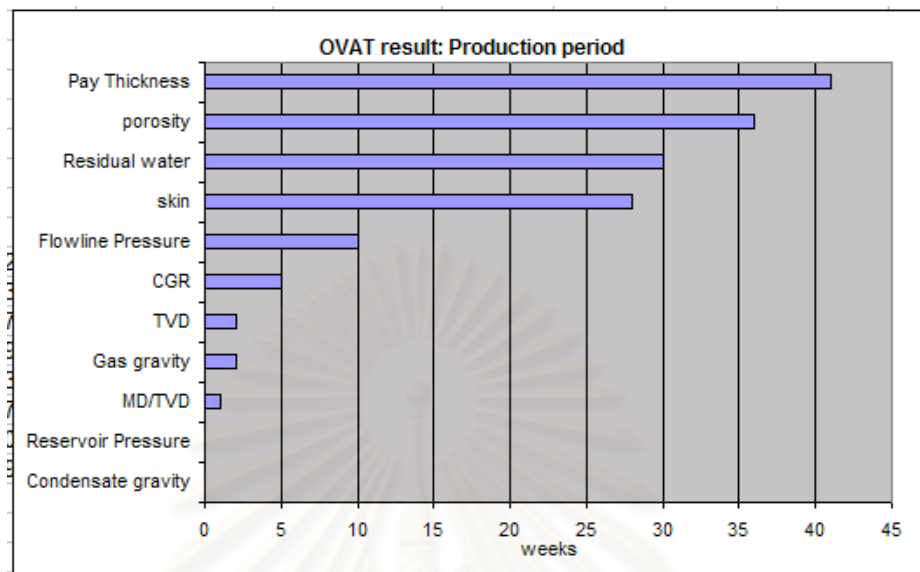
Figure 5.6: OVAT result – production period

For production criteria (figure 5.6), main high effect parameters are pay thickness, porosity, residual water saturation and skin. First three parameters were used for gas volumetric in place calculation. Higher gas in place causes longer production period. Higher skin value causes more extra pressure loss around wellbore. This will lower the production rate and it takes longer production period to produce gas from reservoir.

For cumulative production at abandonment criteria (figure 5.7), main high effect parameters are pay thickness, residual water saturation, porosity and reservoir pressure gradient. First three parameters can refer to gas reserve. Higher reserve results in higher cumulative production at the abandonment. Reservoir pressure gradient is considered as energy of reservoir. Higher reservoir energy refers to higher reservoir ability to flow fluid from down hole to surface which increases the cumulative production at abandonment.
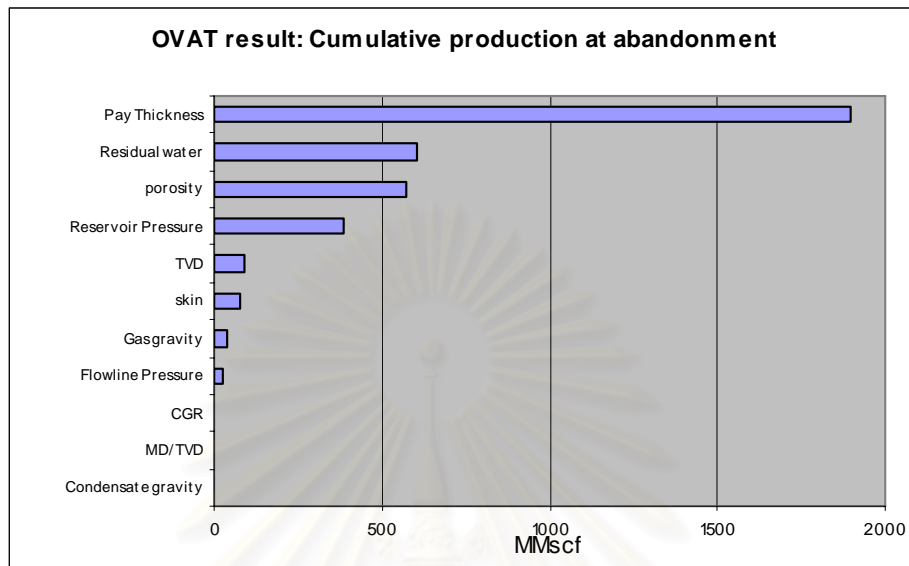
Figure 5.7: OVAT result – cumulative production at abandonment

As a result of OVAT screening process identified by each production profile characteristic parameters, it indicates that the significant high effect parameters to production profile are pay thickness, reservoir pressure gradient, porosity and total skin factor.

From OVAT result, although we can observe the high effect parameters but next section experimental design technique for screening will be introduced to compare the result with OVAT method.

Plackett-Burman design of experiment methodology which is commonly know as screening design was applied to identify effect of each parameter to the result. High value and Low value of each input was expressed as "+1" and "-1" respectively. For example, parameter "gas gravity" if the experiment case represent "+1" in the table meaning the input value for gas gravity for that case is at the high level that equal to 1.0684, the P90 value of gas gravity where as "-1" refers to 0.96478, the P10 value of gas gravity.

Table 5.5: Plackett-Burman design

Case	Gas gravity	CGR	Condensate gravity	Reservoir Pressure	porosity	Pay Thickness	MD/TVD	TVD	Residual water	skin	Flowline Pressure
1	-1	-1	-1	1	1	1	-1	1	1	-1	1
2	-1	1	1	1	-1	1	1	-1	1	-1	-1
3	-1	1	1	-1	1	-1	-1	-1	1	1	1
4	1	-1	-1	-1	1	1	1	-1	1	1	-1
5	1	1	-1	1	-1	-1	-1	1	1	1	-1
6	-1	1	-1	-1	-1	1	1	1	-1	1	1
7	1	-1	1	-1	-1	-1	1	1	1	-1	1
8	1	1	1	-1	1	1	-1	1	-1	-1	-1
9	1	-1	1	1	-1	1	-1	-1	-1	1	1
10	1	1	-1	1	1	-1	1	-1	-1	-1	1
11	-1	-1	1	1	1	-1	1	1	-1	1	-1
12	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1

Table 5.5 represents series of experiment which contains the input level of each parameter using Plackett – Burman technique. After transfer input to simulation model via Openserver option, production prediction for each case was run and the results of production profile characteristics were summarized in table 5.6.

Table 5.6: Plackett-Burman results

Case	Initial gas rate	Production period	Cumulative Gas at abandonment
1	20.4	54	2815
2	8.2	85	1908
3	5.5	27	460
4	10.1	73	2120
5	1.4	57	353
6	3.5	184	2026
7	2.7	35	330
8	13.0	101	3601
9	4.9	198	2729
10	10.7	41	1057
11	9.9	44	1085
12	2.3	53	438

Pareto chart is a tool to identify high effect parameters by ordering main effect of each parameter. Main effect of each parameter is the difference between average results at high value of that parameter and average results at low value which can be expressed as:

Main effect = Average output@ high level input

- Average output@ low level input   (5.3)

Using the results from table 5.6 correlating with level of each input variables for each case, Pareto chart was constructed for three objectives as similar to prior OVAT screening. First is to identify high effect parameters of initial gas rate (figure 5.8). Second is to identify high effect parameters of production period (figure 5.9). Last is to identify high effect parameters of cumulative production at abandonment (figure 5.10)
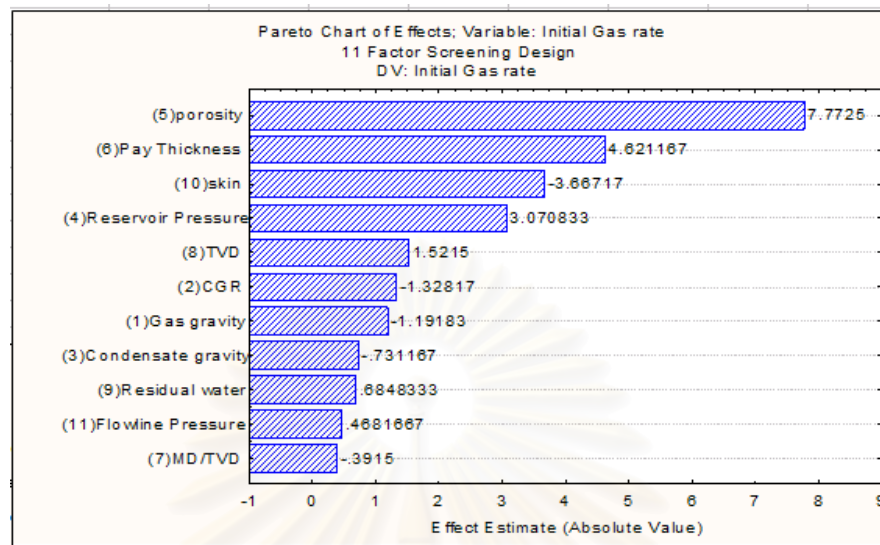
Figure 5.8: Pareto chart for initial gas rate
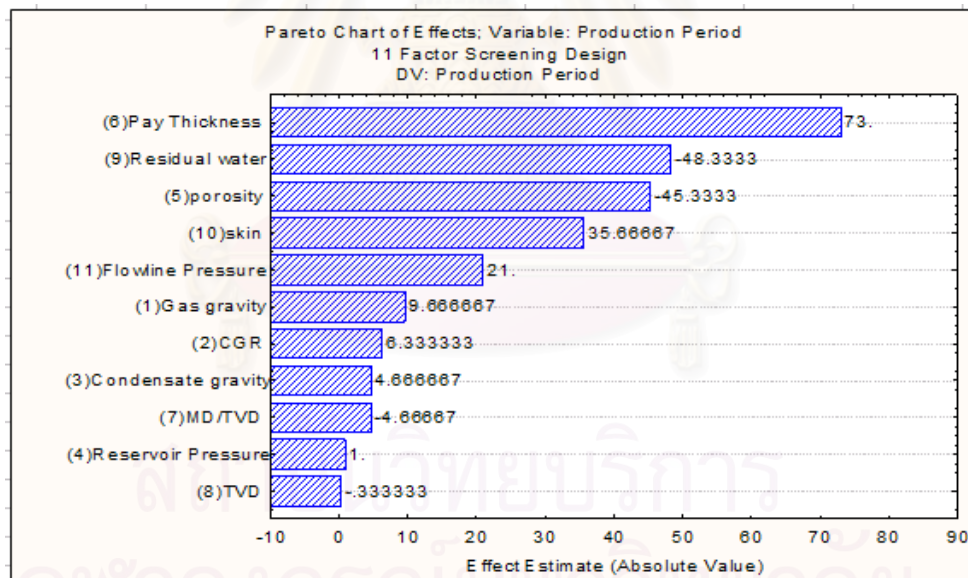
Figure 5.9: Pareto chart for production period
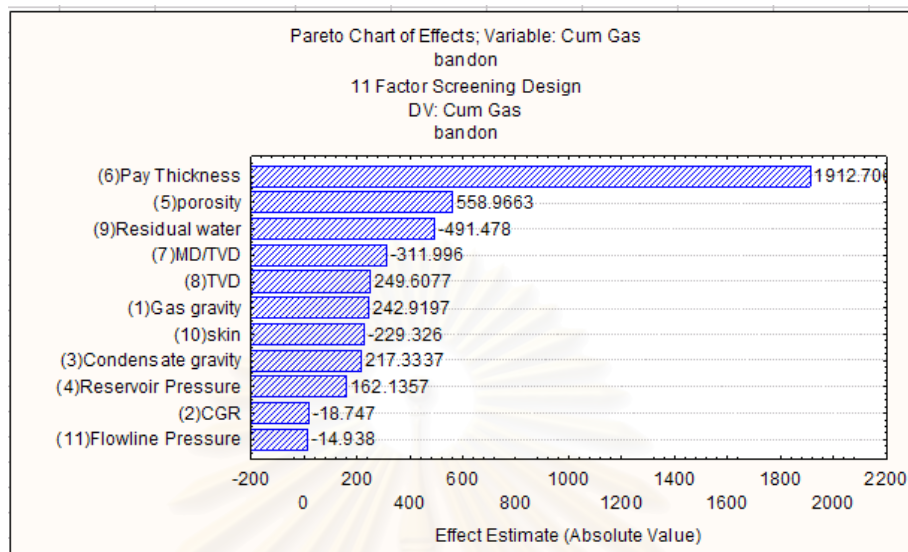
Figure 5.10: Pareto chart for cumulative production at abandonment

Pareto charts rank the high effect parameters by its main effect. It indicates that the significant high effect parameters identify by OVAT method and Plackett Burman for each production profile characteristic parameters are almost the same.

Considering figure 5.7 and figure 5.10, both are OVAT result and Plackett - Burman result for cumulative production at abandonment criteria. MD/TVD shows low effect on OVAT result but it shows some effect on Plackett-Burman technique. This is because the main effect plotted on pareto chart cannot capture correlation between input parameter. By using Plackett - Burman technique, all input parameters have pattern to change their input levels in the same time. Then the main effect for each input parameter was also affected by value of other input parameters. But if we consider the number of simulation runs for Plackett – Burman technique which are less than OVAT method by almost half and its overall results are almost similar, Therefore, Plackett-Burman technique is effectively tool for screening high effect parameter.

By considering both techniques applied for this research, porosity, pay thickness, reservoir pressure gradient, skin and residual water were selected parameters to be considered in the next part, response surface design.

5.2.3 Response surface design

From the previous section, the high effect parameters were obtained from both OVAT analysis and Prackett Burman technique. This section will provide more detail about selected parameters and the response of result using 3-level design.

There are many type of 3-level design. Each design type has different design characteristics or design patterns which may be suitable for some specific objective. Therefore, types of design selection need to be considered carefully. Some discussion of 3-level design types are presented as follow.

The 3-level fractional factorial designs are especially useful for qualitative factor (method, material type, lot, vendor, operator, etc) which have few anticipated significant interactions. If all factors are quantitative (time, temperature, pressure, flow, speed, concentration, etc) and the objective is to evaluate factor interactions, the 3-level fractional factorial design will be very inefficient.

Box-Behnken design is an efficient and frequently used 3-level design for modeling quantitative factors. This design does not contain any corner points (no mid level input parameter) in the design space, which may or may not be concern. In some experiments where corner points are infeasible, the Box-Behnken may be an attractive alternative. This design allows for estimating linear effects, quadratic effects and all linear 2-way interactions. But when the number of factors is greater than 4, the Box-Behnken design will be less efficient with regard to the number of runs than the central composite design. Central composite design was then selected type of design to apply 5 high effect parameters obtained from the previous section.

Central composite design (CCD) or Box – Wilson design is a very flexible and efficient second-order modeling design for qualitative factors. This type of design contain star points (refer to chapter III). These star points are chosen to produce rotatability, which simply implies that the predicted response is capable of being estimated with equal variance regardless of the direction from the center of the design space.

Because star points will be higher than high level or lower than low level value, then it is not suitable for some parameters in this research such as for

parameter pay thickness if we apply normal star point value, the minimum value will be negative value which is not possible. Then this research apply CCD face center type to design the experiment in order to force the star points to stay within the range of high level and low level.

Face center type will not have rotatability and will suffer some loss of orthogonality for quadratic terms. However, it has been used successfully in numerous case studies.

Table 5.7 summarizes the series of input level for all parameters by apply CCD face center type in order to run and get the output cover range and also capture the curvature of the result.

Table 5.7: Central composite design – Face center

Case	Reservoir Pressure	Porosity	Pay Thickness	Residual water	Skin
1	-1	-1	-1	-1	-1
2	-1	-1	-1	-1	1
3	-1	-1	-1	1	-1
4	-1	-1	-1	1	1
5	-1	-1	1	-1	-1
6	-1	-1	1	-1	1
7	-1	-1	1	1	-1
8	-1	-1	1	1	1
9	-1	1	-1	-1	-1
10	-1	1	-1	-1	1
11	-1	1	-1	1	-1
12	-1	1	-1	1	1
13	-1	1	1	-1	-1
14	-1	1	1	-1	1
15	-1	1	1	1	-1
16	-1	1	1	1	1
17	1	-1	-1	-1	-1
18	1	-1	-1	-1	1
19	1	-1	-1	1	-1
20	1	-1	-1	1	1
21	1	-1	1	-1	-1
22	1	-1	1	-1	1
23	1	-1	1	1	-1
24	1	-1	1	1	1
25	1	1	-1	-1	-1
26	1	1	-1	-1	1
27	1	1	-1	1	-1

Table 5.7 (continued): Central composite design – Face center

Case	Reservoir Pressure	Porosity	Pay Thickness	Residual water	Skin
28	1	1	-1	1	1
29	1	1	1	-1	-1
30	1	1	1	-1	1
31	1	1	1	1	-1
32	1	1	1	1	1
33	-1	0	0	0	0
34	1	0	0	0	0
35	0	-1	0	0	0
36	0	1	0	0	0
37	0	0	-1	0	0
38	0	0	1	0	0
39	0	0	0	-1	0
40	0	0	0	1	0
41	0	0	0	0	-1
42	0	0	0	0	1
43 (C)	0	0	0	0	0

5.2.4 Surrogate model fitting

After completed running the whole series of experiment, regression technique was applied to fit the result from simulation.

The result from simulation is not only one value. But it is production profile which contain gas rate at each time step. In order to fit the response, production rates at the same time step were selected altogether for regression and came up with surrogate model at each time step. This research use timestep size, to capture the response, equal to one week which is suitable for the production period generated by our simulation.

For the equation which applied to fit the response, this research applied 4 types of equation to perform regression and then selected the best fit equation for the surrogate model. The general form of each equation can be expressed as,

- Linear effect equation

$$\hat{y} = b_0 + \sum_{i=1}^{n} b_i x_i \tag{5.4}$$

- Linear effect and Quadratic effect equation

$$\hat{y} = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} b_{ii} x_{ii}^2 \qquad (5.5)$$

- Linear effect and Linear 2-way interactions equation

$$\hat{y} = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n-1} \sum_{2}^{n} b_{ij} x_i x_j \qquad (5.6)$$

- Linear effect , Quadratic effect and Linear 2-way interactions equation

$$\hat{y} = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} b_{ii} x_{ii}^2 + \sum_{i=1}^{n-1} \sum_{2}^{n} b_{ij} x_i x_j \qquad (5.7)$$

Next section provides sample case of regression fitting. Table 5.8 shows the series of experiment. Each experiment contains input value for each variable and the last column presents the result at first time step of each experiment case. By applying regression technique, equation coefficients can be archived.

Table 5.8: First timestep regression input

Case	Reservoir pressure gradient (ppg)	porosity (fraction)	Pay Thickness (ft)	Residual water (fraction)	skin	Gas rate at first time step (MMscf/d)
1	7.750	0.132	29.2	0.320	-0.14	2.443
2	7.750	0.132	29.2	0.320	14.70	1.002
3	7.750	0.132	29.2	0.564	-0.14	2.443
4	7.750	0.132	29.2	0.564	14.70	1.002
5	7.750	0.132	117.0	0.320	-0.14	6.811
6	7.750	0.132	117.0	0.320	14.70	3.549
7	7.750	0.132	117.0	0.564	-0.14	6.811
8	7.750	0.132	117.0	0.564	14.70	3.549
9	7.750	0.184	29.2	0.320	-0.14	9.204
10	7.750	0.184	29.2	0.320	14.70	6.46
11	7.750	0.184	29.2	0.564	-0.14	9.204
12	7.750	0.184	29.2	0.564	14.70	6.46
13	7.750	0.184	117.0	0.320	-0.14	12.476
14	7.750	0.184	117.0	0.320	14.70	10.881
15	7.750	0.184	117.0	0.564	-0.14	12.476
16	7.750	0.184	117.0	0.564	14.70	10.881
17	10.463	0.132	29.2	0.320	-0.14	3.469
18	10.463	0.132	29.2	0.320	14.70	1.505
19	10.463	0.132	29.2	0.564	-0.14	3.469
20	10.463	0.132	29.2	0.564	14.70	1.505
21	10.463	0.132	117.0	0.320	-0.14	9.649
22	10.463	0.132	117.0	0.320	14.70	5.209
23	10.463	0.132	117.0	0.564	-0.14	9.649
24	10.463	0.132	117.0	0.564	14.70	5.209
25	10.463	0.184	29.2	0.320	-0.14	12.944
26	10.463	0.184	29.2	0.320	14.70	9.158
27	10.463	0.184	29.2	0.564	-0.14	12.944
28	10.463	0.184	29.2	0.564	14.70	9.158
29	10.463	0.184	117.0	0.320	-0.14	17.801
30	10.463	0.184	117.0	0.320	14.70	15.491
31	10.463	0.184	117.0	0.564	-0.14	17.801
32	10.463	0.184	117.0	0.564	14.70	15.491
33	7.750	0.155	64.0	0.478	3.00	7.072
34	10.463	0.155	64.0	0.478	3.00	10.027
35	8.930	0.132	64.0	0.478	3.00	4.453
36	8.930	0.184	64.0	0.478	3.00	12.917
37	8.930	0.155	29.2	0.478	3.00	5.032
38	8.930	0.155	117.0	0.478	3.00	10.909
39	8.930	0.155	64.0	0.320	3.00	8.388
40	8.930	0.155	64.0	0.564	3.00	8.388
41	8.930	0.155	64.0	0.478	-0.14	9.473
42	8.930	0.155	64.0	0.478	14.70	5.764
43 (C)	8.930	0.155	64.0	0.478	3.00	8.388

From the regression result, Linear effect, Quadratic effect and Linear 2-way interactions equation which can capture linear effect quadratic effect and effect between correlation of parameters, is the best fit equation base on R-square value. Fitting equation can illustrated as below,

$$
\begin{aligned}
\hat{y} = {} & b_0 + b_1 x_1 + b_{11} x_1^2 + b_2 x_2 + b_{22} x_2^2 + b_3 x_3 + b_{33} x_3^2 + b_4 x_4 + b_{44} x_4^2 + b_5 x_5 + b_{55} x_5^2 \\
& + b_{12} x_1 x_2 + b_{13} x_1 x_3 + b_{14} x_1 x_4 + b_{15} x_1 x_5 + b_{23} x_2 x_3 + b_{24} x_2 x_4 + b_{25} x_2 x_5 + b_{34} x_3 x_4 \\
& + b_{35} x_3 x_5 + b_{45} x_4 x_5
\end{aligned}
$$

(5.5)

Where,

X1 is Reservoir pressure gradient (ppg)

X2 is porosity   (fraction)

X3 is pay thickness   (ft)

X4 is residual water   (fraction)

X5 is skin

Coefficient values for the first timestep model are shown in table 5.9. As can be seen from table, R-square values equal to 0.99007. This shows high quality of model fitting.

Table 5.9: Regression coefficient at first timestep

Mean/Interc.	(1)Pressure(L)	Pressure(Q)	(2)Porosity(L)	Porosity(Q)	(3)Pay thickness(L)	Pay thickness(Q)
4.7167	-2.8780	0.0386	-7.4916	-65.7820	0.0399	-0.0004
(4)Residual water(L)	Residual water(Q)	(5)Skin (L)	Skin (Q)	1L by 2L	1L by 3L	1L by 4L
-6.3742	6.4497	-0.0150	0.0023	18.1928	0.0067	0.0115
1L by 5L	2L by 3L	2L by 4L	2L by 5L	3L by 4L	3L by 5L	4L by 5L
-0.0214	0.1040	3.0277	0.1398	0.0023	-0.0004	-0.0106
Model	R-square					
L,Q,LL	0.99007					

After regression process, the obtained equation was tested by apply the equation to calculate the production rate for all series of experiment and then compare the result with input for doing regression.

The percentage error in the last column of table 5.10 is calculated by

$$\%error = \frac{(input\ production - response\ surface\ production)}{input\ production} X\ 100 \qquad (5.6)$$

Table 5.10 compare the production rate of the input for regression and the production rate calculated by coefficient generated from regression.

From the table, although the response surface model might not get the result as exactly to the input value, but from the percentage error between input and response surface model shows the low differentiate. Then this response surface model can be applied to use as proxy model to forecast field production at the first timestep.

Table 5.10: input data and regression result comparison

Case	Real input (MMscf/d)	Regression result (MMscf/d)	% error from input
1	2.443	2.735	11.96
2	1.002	0.616	-38.48
3	2.443	2.707	10.80
4	1.002	0.550	-45.12
5	6.811	6.464	-5.09
6	3.549	3.859	8.75
7	6.811	6.484	-4.80
8	3.549	3.841	8.24
9	9.204	8.804	-4.35
10	6.46	6.793	5.15
11	9.204	8.814	-4.24
12	6.46	6.765	4.72
13	12.476	13.008	4.26
14	10.881	10.511	-3.40
15	12.476	13.066	4.73
16	10.881	10.531	-3.21
17	3.469	3.897	12.35
18	1.505	0.916	-39.12
19	3.469	3.877	11.75
20	1.505	0.857	-43.04
21	9.649	9.216	-4.49
22	5.209	5.749	10.37
23	9.649	9.244	-4.20
24	5.209	5.739	10.17
25	12.944	12.532	-3.18
26	9.158	9.659	5.47
27	12.944	12.550	-3.04
28	9.158	9.639	5.25
29	17.801	18.326	2.95
30	15.491	14.967	-3.38
31	17.801	18.392	3.32
32	15.491	14.995	-3.20
33	7.072	7.175	1.45
34	10.027	9.924	-1.02
35	4.453	4.975	11.71
36	12.917	12.395	-4.04
37	5.032	5.691	13.10
38	10.909	10.250	-6.04
39	8.388	8.386	-0.02
40	8.388	8.390	0.02
41	9.473	8.950	-5.52
42	5.764	6.287	9.07
43	8.388	8.301	-1.04

There are limitations which decrease the fitting quality. Fitted model at the beginning is Linear effect, Quadratic effect and Linear 2-way interactions model (Eq.5.7) which contains high R-square value. Later on, fitting model was changed to the lower required input parameter model because calculation could not be converge due to limitation of input data. Different cases have different production periods. From that reason, some experimental cases which have short production period will have no inputs for processing regression at later time step. The surrogate model for this research is available for 80 weeks of production period. Regression coefficients for other timestep are summarized in table 5.11.

In order to apply surrogate model to generated production profiles, production rate at each timestep was calculated by using the input values of high effect parameters cooperate with regression coefficients for that timestep which mean if we need to construct production profile for 80 weeks, we need to perform 80 calculation processes.

Excel based tool was developed to automate the calculation for the whole 80 timesteps. By inputting values of high effect parameters, this tool will generated the production rate for all timesteps instead of manual calculation.

Table 5.11: Regression coefficient for all timestep

Week	Mean/Interc.	(1)Pressure(L)	Pressure(Q)	(2)Porosity(L)	Porosity(Q)	(3)Pay thickness(L)	Pay thickness(Q)	(4)Residual water(L)	Residual water(Q)	(5)Skin(L)	Skin(Q)	1L by 2L	1L by 3L	1L by 4L	1L by 5L	2L by 3L	2L by 4L	2L by 5L	3L by 4L	3L by 5L	4L by 5L	Model	R-square
1	4.7167	-2.8780	0.0386	-7.4916	-65.7820	0.0399	-0.0004	-6.3742	6.4497	-0.0150	0.0023	18.1928	0.0067	0.0115	-0.0214	0.1040	3.0277	0.1398	0.0023	-0.0004	-0.0106	L,Q,LL	0.99007
2	2.712	-2.489	0.026	7.354	-106.939	0.024	0.000	-4.480	5.972	-0.042	0.002	16.732	0.007	-0.036	-0.019	0.191	-8.285	0.320	0.004	0.000	0.010	L,Q,LL	0.99102
3	1.683	-2.383	0.028	20.298	-146.705	0.012	0.000	-1.738	4.546	-0.062	0.001	15.640	0.007	-0.086	-0.018	0.261	-18.396	0.482	0.005	-0.001	0.025	L,Q,LL	0.99178
4	0.360	-2.204	0.025	33.531	-187.705	0.001	0.000	0.562	3.452	-0.086	0.000	14.570	0.007	-0.125	-0.016	0.327	-27.720	0.648	0.006	-0.001	0.038	L,Q,LL	0.99239
5	-1.079	-1.968	0.021	43.396	-213.575	-0.010	0.000	3.342	1.985	-0.104	0.000	13.458	0.007	-0.180	-0.014	0.385	-37.227	0.797	0.007	-0.001	0.052	L,Q,LL	0.99280
6	-2.721	-1.786	0.019	59.364	-255.245	-0.018	0.000	5.427	1.106	-0.122	-0.001	12.316	0.007	-0.219	-0.013	0.436	-46.179	0.922	0.007	-0.001	0.064	L,Q,LL	0.99304
7	-4.018	-1.606	0.017	66.189	-270.436	-0.028	0.000	9.126	-1.657	-0.132	-0.001	11.285	0.007	-0.263	-0.012	0.484	-54.143	1.025	0.008	-0.001	0.074	L,Q,LL	0.99333
8	-5.480	-1.346	0.011	75.448	-289.211	-0.035	0.000	10.649	-2.054	-0.144	-0.002	10.140	0.007	-0.308	-0.011	0.523	-60.731	1.140	0.007	-0.001	0.084	L,Q,LL	0.99356
9	-6.690	-1.127	0.007	82.565	-301.396	-0.045	0.000	12.793	-3.141	-0.153	-0.002	9.071	0.007	-0.366	-0.010	0.560	-66.960	1.237	0.007	-0.001	0.096	L,Q,LL	0.99360
10	-8.305	-0.789	-0.005	87.969	-312.582	-0.053	0.000	14.669	-4.176	-0.166	-0.003	8.173	0.007	-0.418	-0.009	0.592	-71.883	1.313	0.007	-0.001	0.108	L,Q,LL	0.99356
11	-8.514	-0.753	-0.001	89.277	-311.162	-0.058	0.000	17.105	-6.063	-0.177	-0.003	7.293	0.007	-0.450	-0.008	0.624	-76.161	1.386	0.006	-0.001	0.113	L,Q,LL	0.99373
12	-9.587	-0.511	-0.009	94.497	-322.029	-0.065	0.000	17.952	-6.083	-0.188	-0.003	6.534	0.007	-0.483	-0.008	0.649	-81.300	1.454	0.006	-0.001	0.122	L,Q,LL	0.99381
13	-10.479	-0.279	-0.017	95.094	-320.597	-0.069	0.000	19.395	-6.936	-0.195	-0.003	5.880	0.007	-0.508	-0.007	0.671	-85.262	1.499	0.005	-0.001	0.126	L,Q,LL	0.99380
14	-10.904	-0.164	-0.019	98.132	-322.760	-0.073	0.000	19.968	-6.866	-0.196	-0.003	5.261	0.007	-0.508	-0.006	0.686	-90.385	1.518	0.004	-0.001	0.129	L,Q,LL	0.99400
15	-11.203	-0.053	-0.022	99.115	-320.820	-0.077	0.000	20.433	-6.810	-0.197	-0.003	4.746	0.007	-0.508	-0.006	0.697	-94.541	1.529	0.004	-0.001	0.131	L,Q,LL	0.99417
16	-11.594	0.017	-0.024	104.643	-334.937	-0.079	0.000	20.356	-6.251	-0.201	-0.003	4.293	0.007	-0.507	-0.005	0.708	-97.680	1.515	0.002	-0.001	0.135	L,Q,LL	0.99449
17	-11.564	0.002	-0.021	105.591	-336.867	-0.080	0.000	21.365	-6.992	-0.203	-0.003	3.934	0.007	-0.503	-0.005	0.715	-100.190	1.511	0.001	-0.001	0.135	L,Q,LL	0.99489
18	-11.175	-0.078	-0.014	105.552	-337.182	-0.081	0.000	22.396	-7.789	-0.205	-0.003	3.665	0.007	-0.506	-0.005	0.717	-102.478	1.523	-0.001	-0.001	0.138	L,Q,LL	0.99505
19	-10.748	0.010	-0.019	95.652	-309.822	-0.083	0.000	23.438	-8.924	-0.203	-0.003	3.517	0.007	-0.465	-0.004	0.726	-106.130	1.555	-0.001	-0.001	0.146	L,Q,LL	0.99532
20	-9.429	-0.036	-0.020	84.990	-293.191	-0.076	0.000	20.384	-7.355	-0.168	-0.002	3.751	0.006	-0.347	-0.006	0.699	-95.873	1.379	-0.009	-0.001	0.114	L,Q,LL	0.99639
21	-9.233	-0.085	-0.014	84.441	-289.015	-0.076	0.000	21.559	-8.226	-0.170	-0.002	3.401	0.006	-0.359	-0.005	0.700	-97.305	1.383	-0.012	-0.001	0.114	L,Q,LL	0.99652
22	-9.142	-0.058	-0.013	81.601	-279.308	-0.075	0.000	22.496	-8.892	-0.177	-0.002	3.073	0.006	-0.378	-0.005	0.700	-98.165	1.400	-0.013	-0.001	0.118	L,Q,LL	0.99662
23	-8.872	-0.044	-0.012	77.026	-264.244	-0.075	0.000	23.445	-9.393	-0.188	-0.002	2.789	0.006	-0.414	-0.004	0.700	-99.136	1.414	-0.015	-0.001	0.123	L,Q,LL	0.99661
24	-8.950	0.009	-0.012	75.281	-256.636	-0.074	0.000	24.093	-9.852	-0.193	-0.002	2.473	0.006	-0.428	-0.003	0.698	-99.473	1.413	-0.017	-0.001	0.126	L,Q,LL	0.99653
25	-9.687	0.147	-0.017	77.052	-258.019	-0.075	0.000	24.830	-10.130	-0.197	-0.002	2.136	0.005	-0.459	-0.003	0.693	-100.554	1.409	-0.019	-0.001	0.130	L,Q,LL	0.99663
26	-9.889	0.223	-0.018	76.567	-252.721	-0.074	0.000	24.928	-9.745	-0.196	-0.002	1.826	0.005	-0.489	-0.002	0.689	-101.438	1.402	-0.020	-0.001	0.135	L,Q,LL	0.99652
27	-10.070	0.300	-0.020	76.576	-249.634	-0.075	0.000	24.774	-9.393	-0.194	-0.002	1.548	0.005	-0.501	-0.002	0.684	-101.597	1.372	-0.022	-0.001	0.139	L,Q,LL	0.99644
28	-10.802	0.473	-0.027	77.147	-248.139	-0.074	0.000	24.925	-9.176	-0.197	-0.002	1.254	0.005	-0.516	-0.001	0.680	-102.536	1.381	-0.024	-0.001	0.140	L,Q,LL	0.99643
29	-10.896	0.555	-0.031	75.899	-245.735	-0.075	0.000	24.962	-8.789	-0.196	-0.002	1.197	0.005	-0.507	0.000	0.686	-106.606	1.351	-0.023	-0.001	0.134	L,Q,LL	0.99602
30	-11.187	0.634	-0.033	75.158	-240.867	-0.076	0.000	25.608	-9.063	-0.190	-0.002	0.964	0.005	-0.530	0.000	0.685	-107.883	1.328	-0.023	-0.001	0.133	L,Q,LL	0.99591
31	-11.475	0.738	-0.037	73.875	-238.431	-0.076	0.000	25.838	-8.904	-0.186	-0.002	0.861	0.005	-0.550	0.000	0.684	-109.226	1.325	-0.024	-0.001	0.135	L,Q,LL	0.99579

Table 5.11 (continued): Regression coefficient for all timestep

Week	Mean/Interc.	(1)Pressure(L)	Pressure(Q)	(2)Porosity(L)	Porosity(Q)	(3)Pay thickness(L)	Pay thickness(Q)	(4)Residual water(L)	Residual water(Q)	(5)Skin(L)	Skin(Q)	1L by 2L	1L by 3L	1L by 4L	1L by 5L	2L by 3L	2L by 4L	2L by 5L	3L by 4L	3L by 5L	4L by 5L	Model	R-square
32	-12.246	0.893	-0.043	77.686	-250.445	-0.078	0.000	25.827	-8.534	-0.187	-0.003	0.549	0.004	-0.576	0.001	0.689	-109.449	1.356	-0.026	-0.001	0.132	L,Q,LL	0.99485
33	-12.785	0.873	-0.041	81.094	-242.609	-0.072	0.000	25.947	-7.569	-0.173	-0.001	0.905	0.004	-0.649	-0.001	0.628	-114.280	1.061	-0.024	-0.001	0.158	L,Q,LL	0.99619
34	-13.426	0.982	-0.046	83.908	-246.391	-0.072	0.000	26.145	-7.585	-0.173	-0.001	0.692	0.004	-0.651	0.000	0.620	-115.563	1.029	-0.025	-0.001	0.160	L,Q,LL	0.99605
35	-13.559	1.027	-0.047	84.300	-244.558	-0.073	0.000	26.249	-7.379	-0.172	-0.002	0.530	0.004	-0.662	0.000	0.613	-116.832	1.018	-0.025	-0.001	0.160	L,Q,LL	0.99584
36	-13.680	1.069	-0.049	84.445	-242.325	-0.072	0.000	26.235	-7.227	-0.169	-0.002	0.415	0.004	-0.662	0.000	0.603	-117.635	0.987	-0.026	-0.001	0.161	L,Q,LL	0.99564
37	-13.877	1.136	-0.051	84.484	-238.151	-0.072	0.000	26.135	-6.886	-0.169	-0.002	0.217	0.004	-0.675	0.001	0.593	-117.818	0.963	-0.027	-0.001	0.160	L,Q,LL	0.99534
38	-14.258	1.202	-0.053	86.086	-237.540	-0.072	0.000	26.198	-6.665	-0.164	-0.002	0.023	0.004	-0.689	0.001	0.582	-118.575	0.923	-0.028	0.000	0.160	L,Q,LL	0.99511
39	-12.736	1.024	-0.043	76.098	-214.362	-0.077	0.000	27.890	-4.617	-0.144	-0.002	0.279	0.004	-0.925	-0.001	0.583	-121.258	0.887	-0.038	-0.001	0.181	L,Q,LL	0.99630
40	-11.189	0.824	-0.032	69.412	-194.714	-0.071	0.000	27.228	-4.984	-0.144	-0.002	0.181	0.004	-0.952	0.001	0.581	-120.801	0.847	-0.030	-0.001	0.204	L,Q,LL	0.99678
41	-11.261	0.857	-0.034	69.113	-192.486	-0.071	0.000	27.144	-4.833	-0.142	-0.002	0.118	0.004	-0.954	0.001	0.570	-120.782	0.814	-0.031	-0.001	0.205	L,Q,LL	0.99674
42	-11.668	0.901	-0.034	72.862	-197.648	-0.070	0.000	27.015	-4.460	-0.139	-0.002	-0.095	0.004	-0.965	0.001	0.562	-121.940	0.781	-0.031	-0.001	0.207	L,Q,LL	0.99686
43	-11.562	0.885	-0.034	71.993	-194.915	-0.070	0.000	27.301	-4.590	-0.135	-0.002	-0.097	0.004	-0.970	0.001	0.553	-122.157	0.744	-0.032	-0.001	0.207	L,Q,LL	0.99686
44	-11.866	0.902	-0.034	74.731	-201.347	-0.070	0.000	27.673	-4.936	-0.132	-0.002	-0.202	0.004	-0.968	0.001	0.545	-122.544	0.730	-0.033	-0.001	0.205	L,Q,LL	0.99683
45	-12.048	0.785	-0.027	85.816	-237.171	-0.070	0.000	27.304	-4.367	-0.135	-0.002	-0.240	0.004	-0.969	0.001	0.541	-123.291	0.717	-0.033	-0.001	0.204	L,Q,LL	0.99677
46	-10.555	0.655	-0.022	71.401	-210.861	-0.065	0.000	27.788	-5.052	-0.140	-0.001	0.145	0.003	-0.973	0.002	0.553	-122.537	0.666	-0.033	-0.001	0.202	L,Q,LL	0.99677
47	-5.173	0.266	0	22.227	0	-0.043	0	23.804	0	-0.155	0	0.054	0.004	-0.984	0.002	0.401	-122.897	0.657	-0.036	-0.001	0.197	L,LL	0.99523
48	-5.023	0.267	0	21.375	0	-0.043	0	23.676	0	-0.151	0	-0.003	0.003	-0.972	0.002	0.403	-122.459	0.623	-0.037	-0.001	0.197	L,LL	0.99527
49	-5.027	0.278	0	21.138	0	-0.043	0	23.751	0	-0.144	0	-0.092	0.003	-0.975	0.002	0.403	-122.234	0.585	-0.038	0.000	0.195	L,LL	0.99483
50	-4.797	0.273	0	19.562	0	-0.042	0	23.575	0	-0.142	0	-0.088	0.003	-0.963	0.002	0.404	-121.421	0.569	-0.038	0.000	0.192	L,LL	0.99463
51	-4.609	0.267	0	18.711	0	-0.042	0	23.336	0	-0.138	0	-0.115	0.003	-0.936	0.002	0.405	-121.400	0.549	-0.038	0.000	0.191	L,LL	0.99465
52	-4.498	0.269	0	18.388	0	-0.042	0	23.129	0	-0.135	0	-0.194	0.003	-0.913	0.002	0.407	-121.475	0.528	-0.038	0.000	0.190	L,LL	0.99458
53	-4.941	0.271	0	21.291	0	-0.038	0	23.409	0	-0.128	0	-0.238	0.003	-0.909	0.002	0.381	-121.279	0.473	-0.041	0.000	0.181	L,LL	0.99553
54	-4.876	0.267	0	21.516	0	-0.038	0	23.285	0	-0.125	0	-0.296	0.003	-0.877	0.003	0.381	-122.377	0.457	-0.041	0.000	0.178	L,LL	0.99558
55	-4.857	0.275	0	21.713	0	-0.038	0	23.129	0	-0.122	0	-0.406	0.003	-0.862	0.003	0.382	-122.213	0.428	-0.041	0.000	0.177	L,LL	0.99554
56	-4.779	0.309	0	15.834	0	-0.037	0	23.955	0	-0.115	0	-0.542	0.003	-0.784	0.003	0.439	-122.624	0.397	-0.054	0.000	0.186	L,LL	0.99569
57	-4.746	0.313	0	14.922	0	-0.036	0	23.933	0	-0.111	0	-0.553	0.002	-0.770	0.003	0.440	-122.331	0.374	-0.056	0.000	0.186	L,LL	0.99587
58	-3.754	0.238	0	12.496	0	-0.042	0	23.715	0	-0.109	0	-0.474	0.003	-0.742	0.002	0.450	-123.290	0.370	-0.055	0.000	0.190	L,LL	0.99599
59	-11.860	0.653	0	33.298	0	0.030	0	26.595	0	-0.118	0	-0.428	-0.001	-0.695	0.003	0.266	-124.049	0.327	-0.082	0.000	0.179	L,LL	0.99664
60	-12.133	0.676	0	34.409	0	0.031	0	26.743	0	-0.118	0	-0.544	-0.001	-0.688	0.003	0.262	-124.729	0.316	-0.083	0.000	0.179	L,LL	0.99697

Table 5.11 (continued): Regression coefficient for all timestep

Week	Mean/Interc.	(1)Pressure(L)	Pressure(Q)	(2)Porosity(L)	Porosity(Q)	(3)Pay thickness(L)	Pay thickness(Q)	(4)Residual water(L)	Residual water(Q)	(5)Skin(L)	Skin(Q)	1L by 2L	1L by 3L	1L by 4L	1L by 5L	2L by 3L	2L by 4L	2L by 5L	3L by 4L	3L by 5L	4L by 5L	Model	R-square
61	-12.575	0.708	0	36.064	0	0.034	0	27.289	0	-0.124	0	-0.656	-0.001	-0.698	0.004	0.256	-127.116	0.329	-0.084	0.000	0.182	L,LL	0.99729
62	-12.786	0.740	0	38.512	0	0.032	0	28.309	0	-0.153	0	-0.939	-0.001	-0.738	0.005	0.261	-133.320	0.420	-0.084	0.000	0.202	L,LL	0.99796
63	-1.0222	0.16682	0	9.74919	0	0.0230	0	-6.0266	0	0.0009	0	0	0	0	0	0	0	0	0	0	0	L	0.86354
64	-0.8699	0.16143	0	8.8851	0	0.0227	0	-6.0209	0	0.0022	0	0	0	0	0	0	0	0	0	0	0	L	0.85967
65	-0.7177	0.15510	0	8.0733	0	0.0223	0	-5.9950	0	0.0033	0	0	0	0	0	0	0	0	0	0	0	L	0.85680
66	-0.5929	0.15037	0	7.3571	0	0.0220	0	-5.9797	0	0.0044	0	0	0	0	0	0	0	0	0	0	0	L	0.85422
67	-0.4395	0.14625	0	6.4825	0	0.0217	0	-5.9916	0	0.0054	0	0	0	0	0	0	0	0	0	0	0	L	0.84890
68	-0.4865	0.10828	0	7.8376	0	0.0212	0	-5.5460	0	0.0100	0	0	0	0	0	0	0	0	0	0	0	L	0.85406
69	-0.3021	0.10127	0	6.9486	0	0.0208	0	-5.5569	0	0.0110	0	0	0	0	0	0	0	0	0	0	0	L	0.84722
70	0.0170	0.0893	0	5.6913	0	0.0204	0	-5.6340	0	0.0115	0	0	0	0	0	0	0	0	0	0	0	L	0.82991
71	-2.1900	0.14854	0	12.3441	0	0.0205	0	-4.1414	0	0.0215	0	0	0	0	0	0	0	0	0	0	0	L	0.92803
72	-2.0419	0.14431	0	11.4846	0	0.0202	0	-4.1364	0	0.0223	0	0	0	0	0	0	0	0	0	0	0	L	0.92576
73	-1.9112	0.13936	0	10.7422	0	0.0198	0	-4.1081	0	0.0234	0	0	0	0	0	0	0	0	0	0	0	L	0.92436
74	-1.7652	0.13515	0	9.9084	0	0.0195	0	-4.1050	0	0.0244	0	0	0	0	0	0	0	0	0	0	0	L	0.92141
75	-1.6319	0.13088	0	9.1243	0	0.0192	0	-4.0955	0	0.0256	0	0	0	0	0	0	0	0	0	0	0	L	0.91913
76	-1.4955	0.12468	0	8.3465	0	0.0189	0	-4.0511	0	0.0263	0	0	0	0	0	0	0	0	0	0	0	L	0.90838
77	-1.8325	0.15442	0	7.1112	0	0.0193	0	-3.4052	0	0.0204	0	0	0	0	0	0	0	0	0	0	0	L	0.92341
78	-1.3571	0.13947	0	6.7410	0	0.0172	0	-3.5571	0	0.0177	0	0	0	0	0	0	0	0	0	0	0	L	0.93643
79	-1.2368	0.13552	0	6.0218	0	0.0169	0	-3.5392	0	0.0187	0	0	0	0	0	0	0	0	0	0	0	L	0.93405
80	-1.3726	0.13919	0	5.4993	0	0.0186	0	-3.8761	0	0.0259	0	0	0	0	0	0	0	0	0	0	0	L	0.92492

5.3 Surrogate model testing

This section, random numbers of input were generated to test the quality of surrogate model by comparing production profile from simulation and production profile from surrogate model.

Random number of input were used to calculate the production profile at each timestep and the same input numbers were transferred to simulator and then generated the production profile and plotted both profiles together to compare the result.

Figure 5.11 to 5.17 show input value for both simulation and surrogate models and also show production profiles generated by both methods.

Case 1

Reservoir pressure gradient (ppg)	Porosity (fraction)	Pay Thickness (ft)	Residual water (fraction)	Skin
9.000	0.160	80.0	0.500	8.00
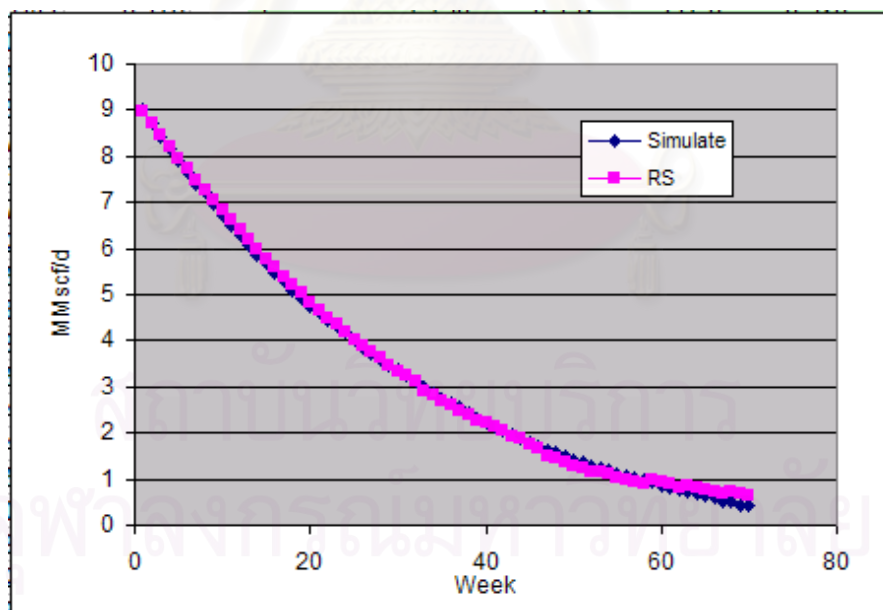
Figure 5.11: Surrogate model and Simulation comparison (Case 1)

Case 2

Reservoir pressure gradient (ppg)	Porosity (fraction)	Pay Thickness (ft)	Residual water (fraction)	Skin
9.000	0.170	100.0	0.400	12.00
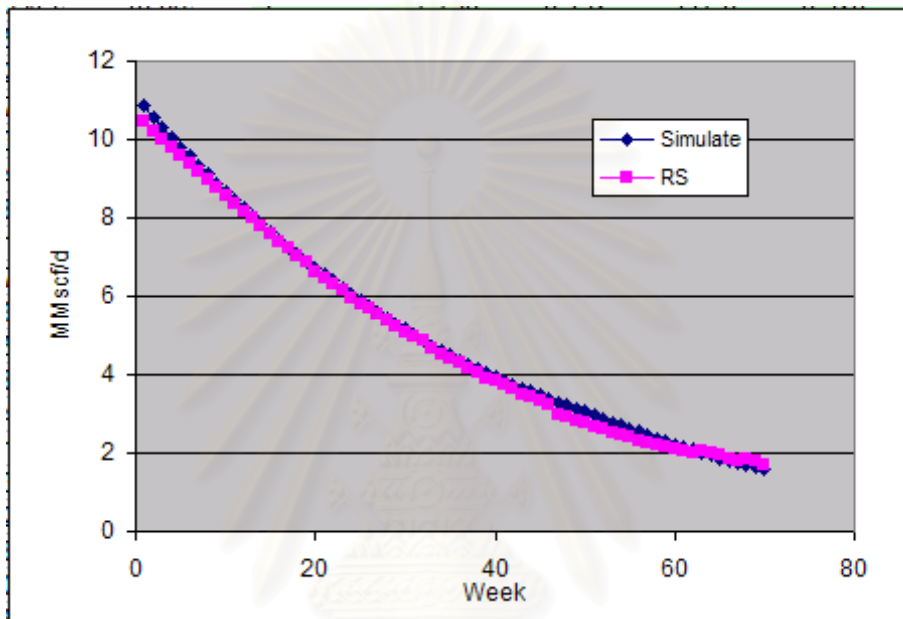
Figure 5.12: Surrogate model and Simulation comparison (Case 2)

For the case 1 and case 2, production profile from both surrogate model and simulation are similar. There are some parts that one slightly different but for the whole profile it shows high fitting quality.

Case 3

Reservoir pressure gradient (ppg)	Porosity (fraction)	Pay Thickness (ft)	Residual water (fraction)	Skin
8.000	0.170	95.0	0.380	2.00
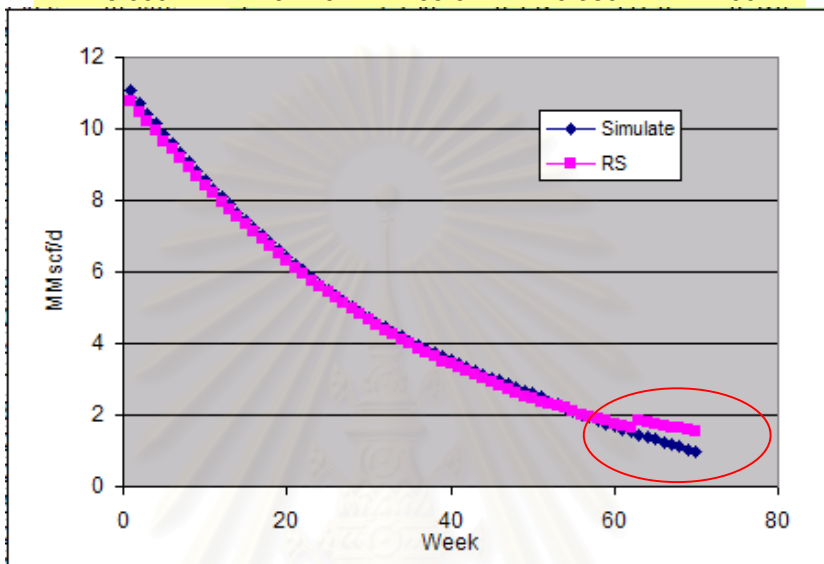
Figure 5.13: Surrogate model and Simulation comparison (Case 3)

Case 4

Reservoir pressure gradient (ppg)	Porosity (fraction)	Pay thickness (ft)	Residual water (fraction)	skin
10	0.180	80.0	0.500	12.00
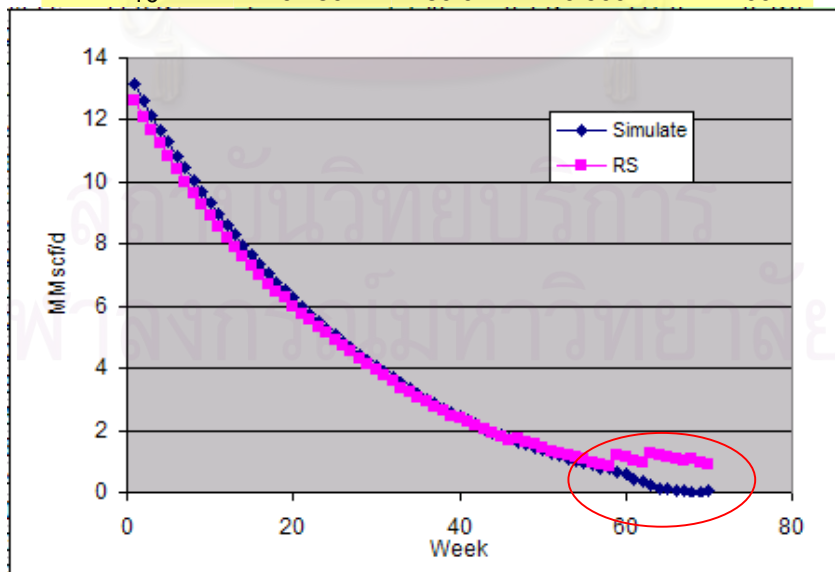
Figure 5.14: Surrogate model and Simulation comparison (Case 4)

As can be seen from figure 5.13 and 5.14, the final part of profile has greater different than other part. This is because the fitting model in the final part is linear effect model and has lower R-square value than other part as a result of greater difference between surrogate model and simulation one.

Case 5

Reservoir pressure gradient (ppg)	Porosity (fraction)	Pay Thickness (ft)	Residual water (fraction)	Skin
8.500	0.170	35.0	0.400	5.00
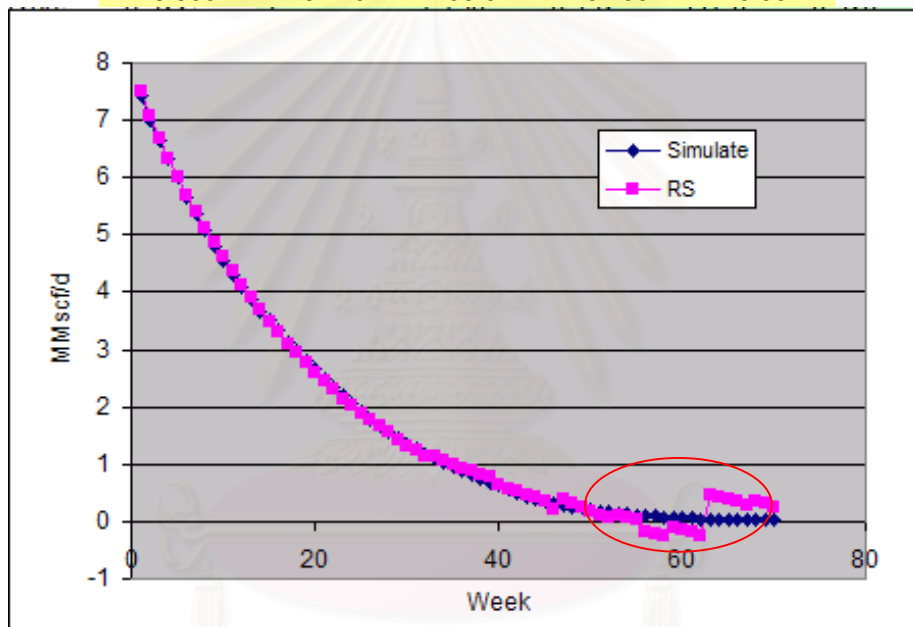
Figure 5.15: Surrogate model and Simulation comparison (Case 5)

Figure 5.15 shows that the production profile from surrogate model is different from simulation since this model cannot automatically stop calculating. Because, the surrogate model is a series of production rate equation for each timestep and have no algorithm to stop production forecasting. It will generate the production rates for all timestep although the production profile decline lower than production cutoff rate. In order to use this surrogate model, user needs to carefully set the production cutoff criteria and cut out the production profile later than cutoff value.

Case 6

Reservoir pressure gradient (ppg)	Porosity (fraction)	Pay thickness (ft)	Residual water (fraction)	Skin
10.000	0.140	60.0	0.500	10.00
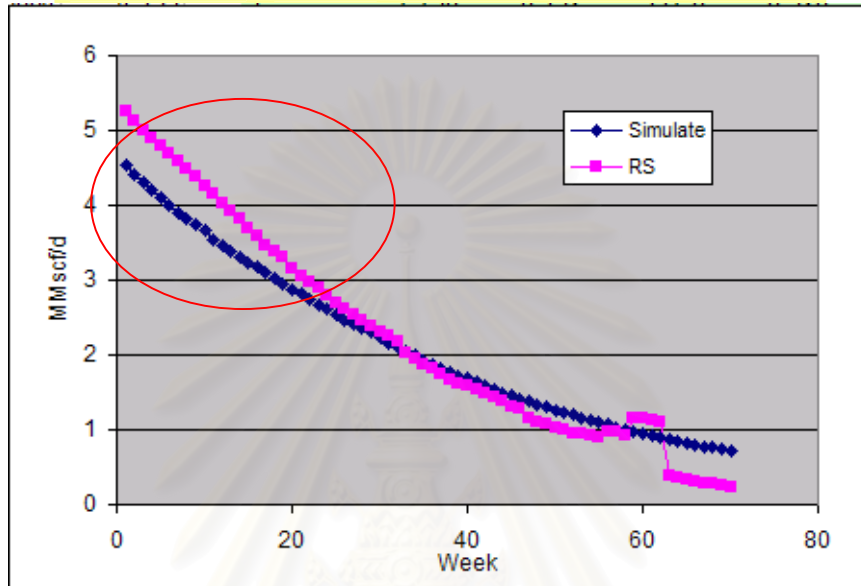
Figure 5.16: Surrogate model and Simulation comparison (Case 6)

Case 7

Reservoir pressure gradient (ppg)	Porosity (fraction)	Pay thickness (ft)	Residual water (fraction)	Skin
9.000	0.140	75.0	0.530	8.00
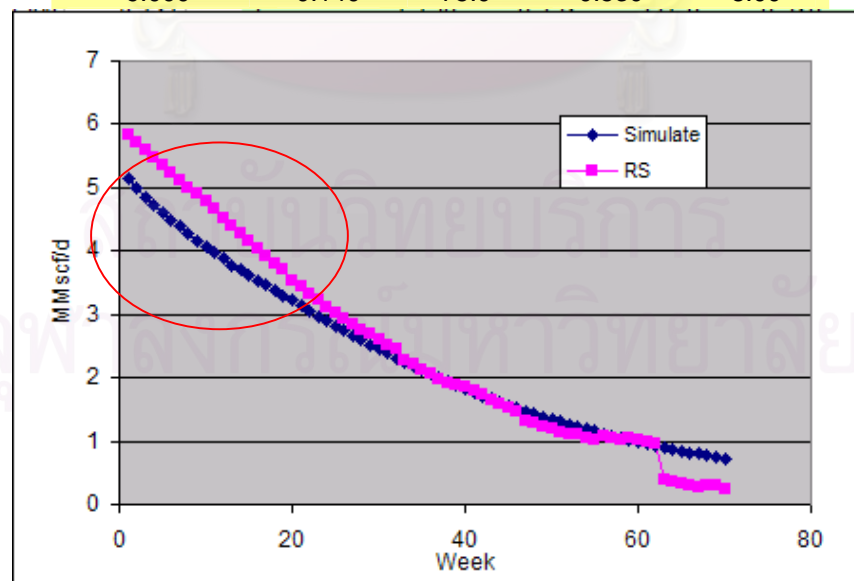
Figure 5.17: Surrogate model and Simulation comparison (Case 7)

As seen from figure 5.16 and 5.17 there is early section that the result from surrogate model does not match with simulation data. Because during regression process, some peak value were smoother out by regression equation. Then, applying this technique needs to care about its limitation.

Figure 5.11 to 5.17 show production profile comparison between surrogate model and simulation result. Most of production rate generated by surrogate model show the same trend as simulation results and have slightly different production rates between two models at each time step. Therefore this surrogate model can be used for production prediction.

5.4 Surrogate model application

As discuss earlier, the objective of this research is to forecast field production. So we developed surrogate model to forecast production profile based on high effect parameters. But it still has limitation of use, simulation model would stop at certain period while our surrogate model still continue forecasting. This requires suitable decision to select production period.

This section shows how to apply this model to forecast production. By applying this surrogate model to group of wells which have surface condition similar to this surrogate model. Total field forecast is the summation of individual well production forecast generated by the surrogate model.

Excel base tool was developed to simplify the process of calculation. Monte Carlo technique might be applied to study uncertainties but it require carefully use due to limitation as discuss above. Figure 5.18 shows flow chart of calculation.
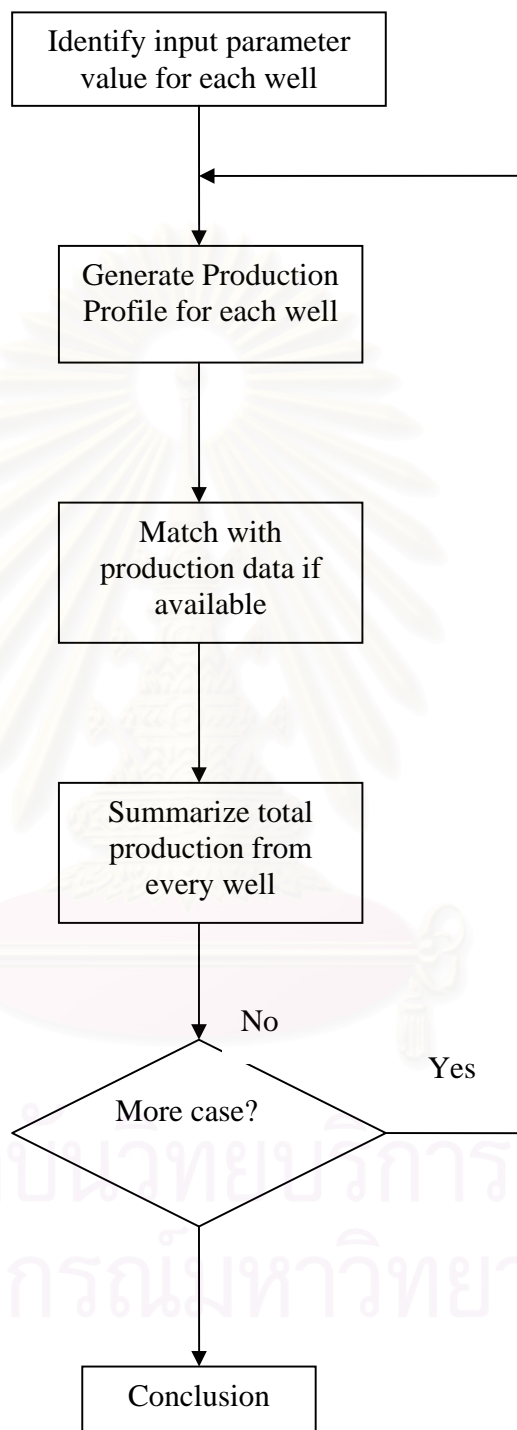
Figure 5.18: Surrogate model application flowchart

The calculation process starts by obtaining parameter input values from the field. Then production profile is generated by using the surrogate model. If there is historical production data available, history matching can be done by adjusting the input value. Finally, production from each wells are added up to total production.

Next section presents the results of applying excel based tool to forecast production from field by comparing the result from surrogate model with historical production data from this field. This field starts its development at October 2004 with 11 production wells. But since Jan 2004, it indicated that there were 4 wells that have poor production performance such as show in figure 5.19. Then, 7 wells were selected for production forecasting.
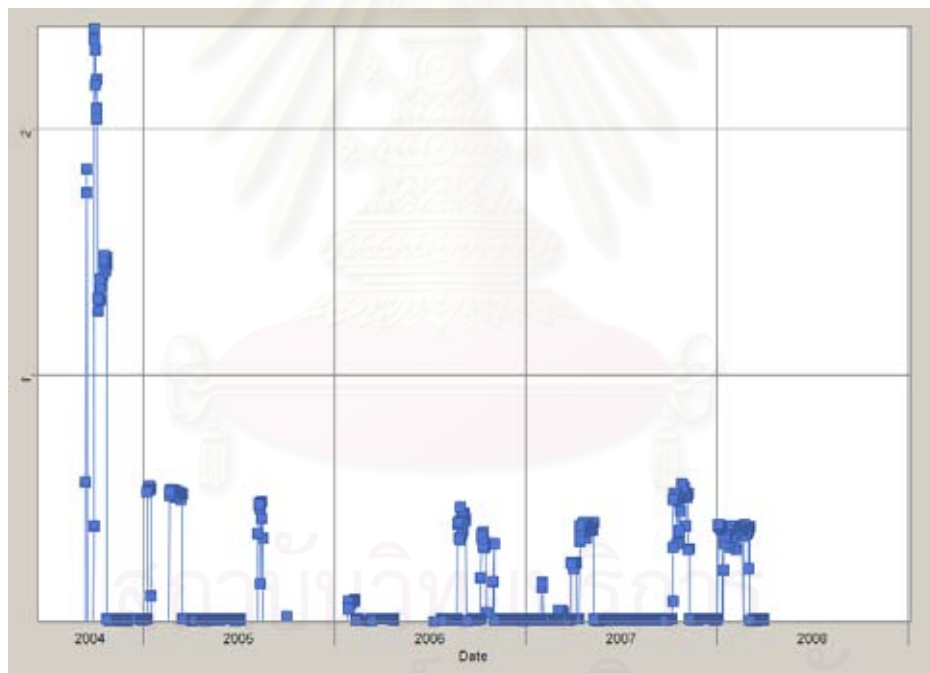
Figure 5.19: Poor Production well

The required parameters for history matching process are reservoir pressure gradient, skin, pay thickness and residual water saturation. This surrogate model was developed based on production from group of pay sands in one well. Each pay sands may contain different reservoir properties. Therefore, only exact data for performing history match is pay thickness which is the total thickness of pay sands in well. Other

input parameters values should use their weight average values of individual pay thickness. Figure 5.20 to 5.26 show each well production forecast compare with its initial production.
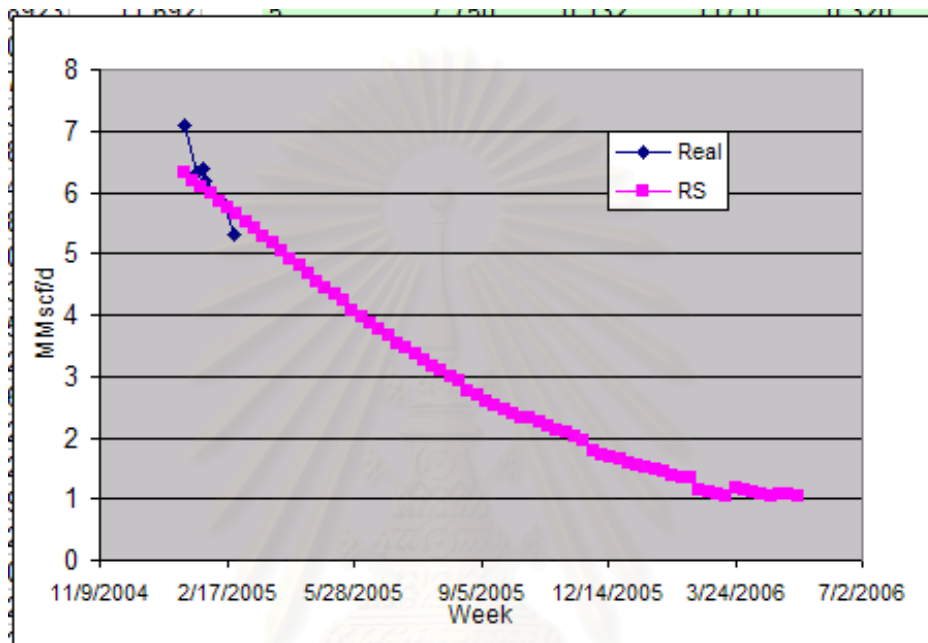
Figure 5.20: Well I production forecast
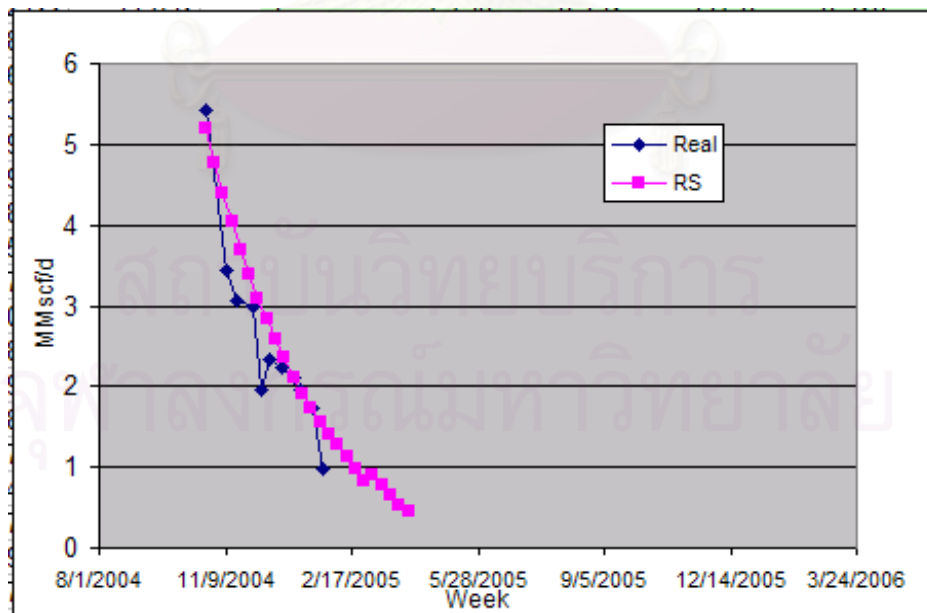
Figure 5.21: Well II production forecast
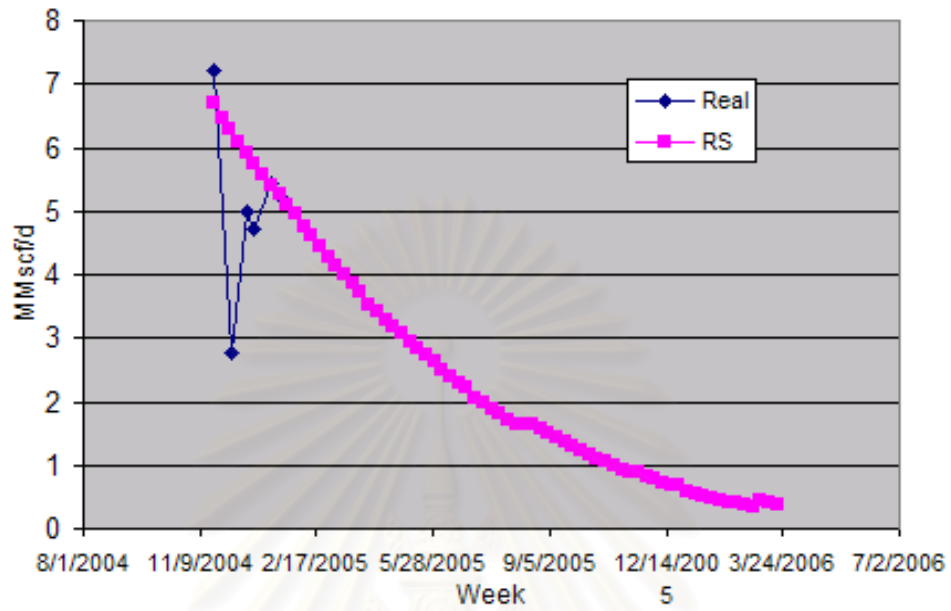
Figure 5.22: Well III production forecast
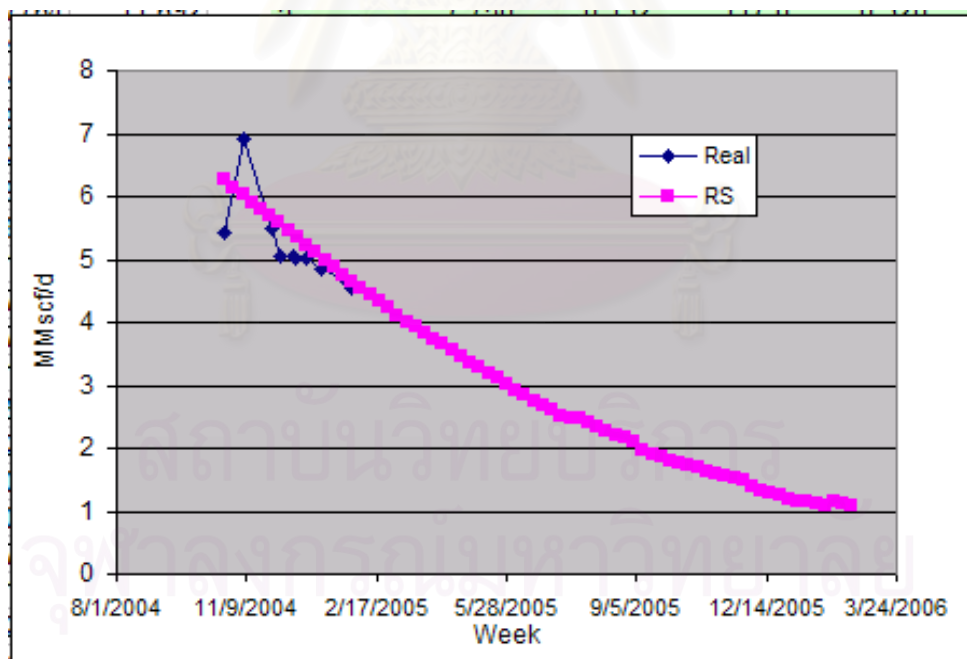
Figure 5.23: Well IV production forecast
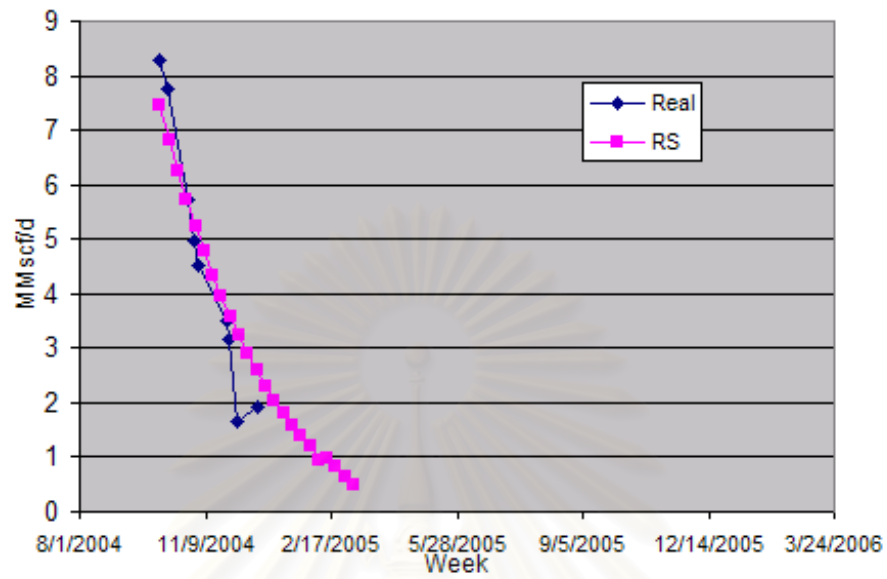
Figure 5.24: Well V production forecast
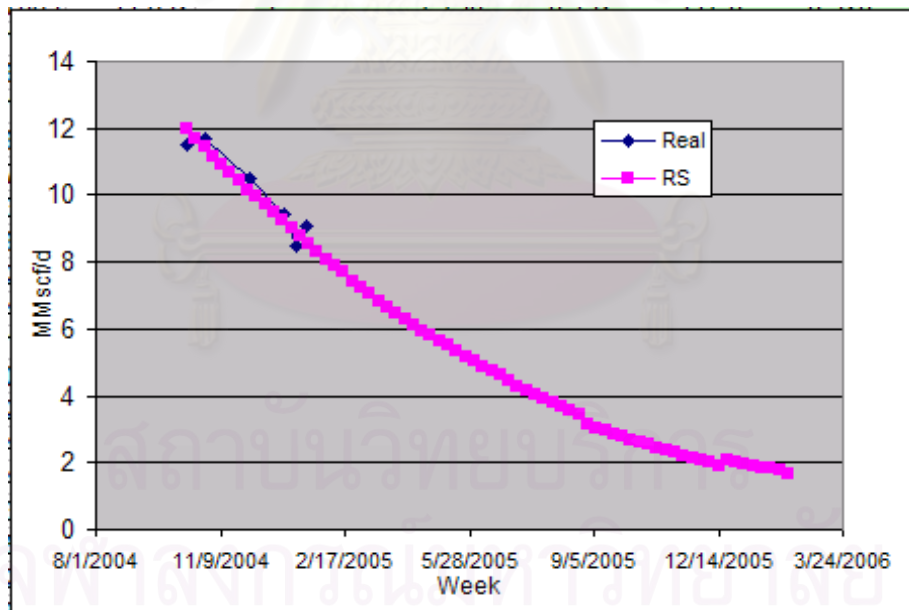
Figure 5.25: Well VI production forecast
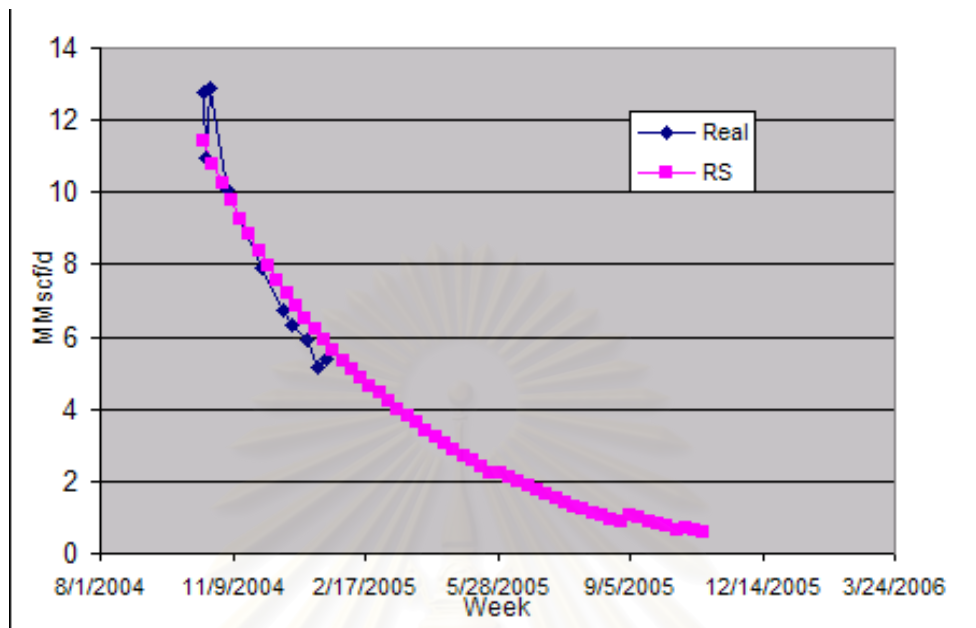
Figure 5.26: Well VII production forecast

Table 5.12 Summarized matching parameter value from every well

	Start date	Delay Start (weeks)	Reservoir pressure gradient (ppg)	porosity (fraction)	Pay Thickness(ft)	Residual water (fraction)	skin
Well 1	1/14/2005	16	8.1	0.15	78	0.402	10
Well 2	10/24/2004	4	8.8	0.15	34	0.58	5
Well 3	11/21/2004	8	8.516	0.161	64	0.476	0
Well 4	10/23/2004	4	7.9	0.152	92	0.45	14
Well 5	10/4/2004	1	8	0.17	30	0.57	3
Well 6	10/13/2004	2	8.94	0.1675	112	0.428	3
Well 7	10/18/2004	3	8.5	0.179	60	0.414	0

Using values of each parameter from table 5.12 imported to excel base tool the production profile from this group of wells can be generated as figure 5.27.
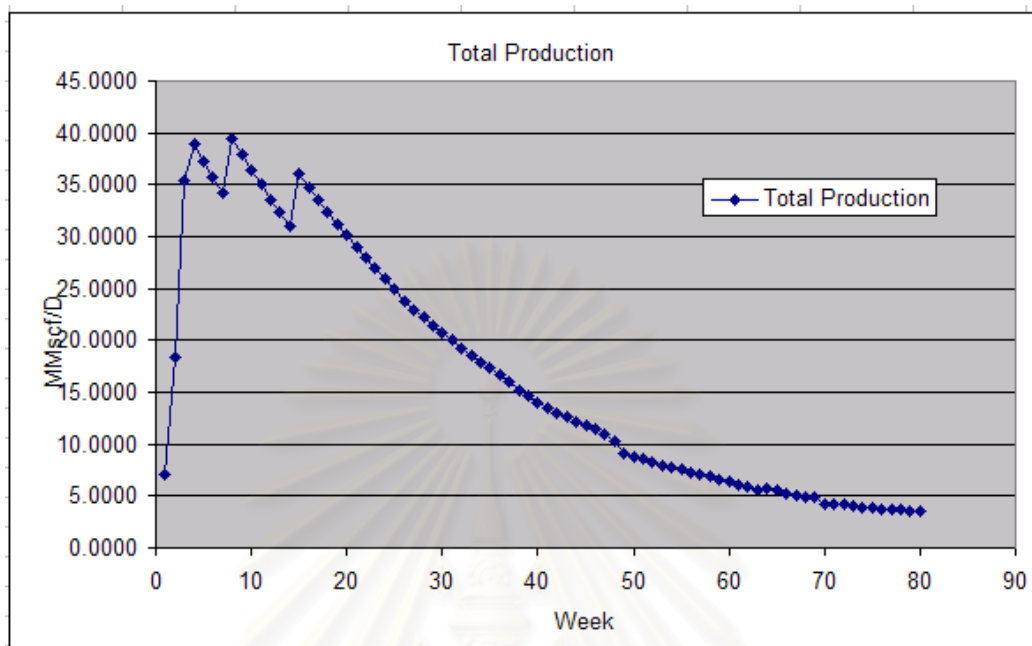
Figure 5.27: Production profile forecast
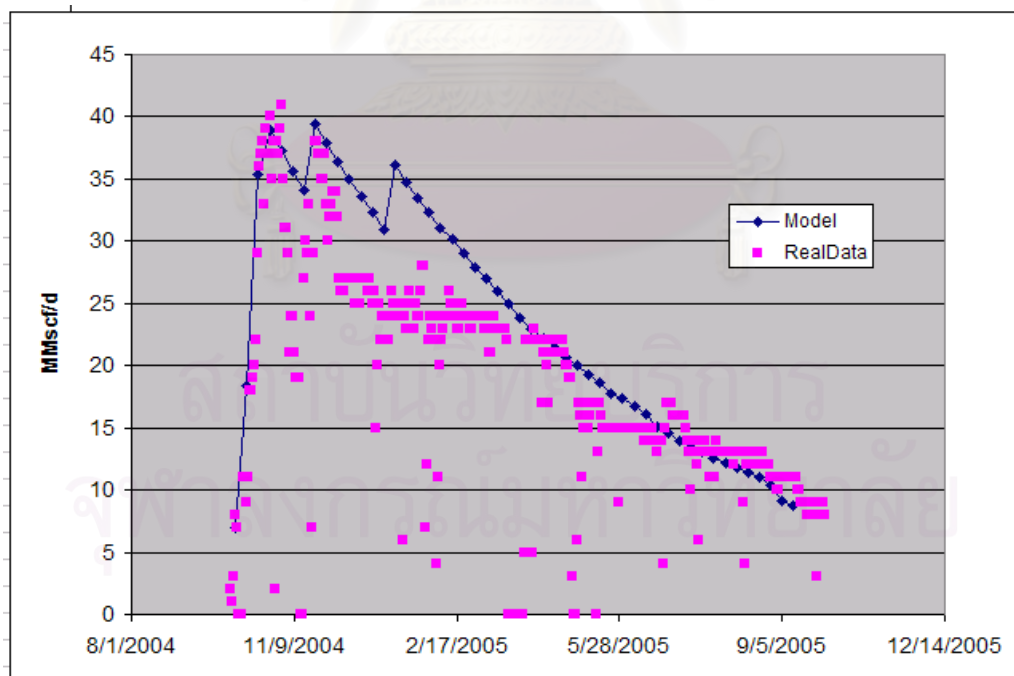
Figure5.28: Comparison between field productions with surrogate model result

Figure 5.28 compare production profile from historical production data by plotting together with production profile generated by response surface model. As can be seen from the figure, both production profiles have the same trend and some slightly differences. Therefore, this technique was proved that it can apply to forecast field production

CHAPTER VI

CONCLUSIONS AND RECOMMENDATIONS

This research focuses on gas production forecast from group of wells which have similar surface operating condition and using reference data obtained from "P" field which is the one of major gas fields in the Gulf of Thailand.

The experimental design has been applied to this research for two purposes. First is screening purpose. The objective of this design is to screen the variables which have high effect on the result generated by Integrated Production Modeling toolkits application. Plackett-Burman design which commonly known as screening design was used to screen the main 11 input parameters for IPM simulator, namely gas gravity, condensate gas ratio, condensate gravity, reservoir pressure gradient, porosity, pay thickness, MD/TVD, TVD, residual water saturation, total skin factor and flowline pressure. Other input parameters for base case simulation were the average values obtained from "P" field.

One variable at a time (OVAT), traditional method for screening high effect parameters, was also including in this research to compare with screening design results. IPM output is not a single output value but it is a production profile containing production rate at each timestep. This creates complexity in identifying high effect input parameters. In order to identify high effect parameters, production profile characteristic parameters were introduced to be considered as criteria of result. These parameters include initial gas rate, production period and cumulative production at abandonment.

As a result of screening process, it indicates that the significant high effect parameters identified by OVAT method and Plackett-Burman design for each production profile characteristic parameters are almost the same. But the number of simulation runs for Plackett-Burman design are much lower than OVAT which means that Plackett-Burman design technique is an effective tool for screening high effect parameters.

From the result of both techniques, porosity, pay thickness, reservoir pressure gradient, total skin factor and residual water saturation were the selected parameters to be considered in the next experimental design to determine production forecast.

The second purpose is to develop surrogate model. This will be achieved by performing response surface design which allows us to estimate the interaction and even quadratic effect, and therefore give us an idea of the (local) shape of the response surface we are investigating.

This research apply central composite design (CCD) which is a very flexible and efficient second-order modeling design for quantitative factors to do experiment covering entire response. This CCD is face center type. Because we need to control the star point to stay in the range of high and low level.

After running simulation, regression techniques are applied for fitting a response of simulation. There are 4 types of equation to capture the effect of high effect parameters to the result including,

- Linear effect equation
- Linear effect and Quadratic effect equation
- Linear effect and Linear 2-way interactions equation
- Linear effect, Quadratic effect and Linear 2-way interactions equation

From the results, developed surrogate model has high fitting quality based on R-square value up to 80 weeks of production period. At the early timestep, fitting model can be complicated models such as Linear effect, Quadratic effect and Linear 2-way interactions equation but late timestep, some experimental cases which have shorter production period have no inputs for processing regression then the complicated model can not be used.

Regression process also could not fit all of the exact value of input. Some peak values were smooth out by fitting equation. So, using the model need to apply it carefully. But for the test case and history matching process it shows high accuracy of estimation. Therefore, this surrogate model might be applied for forecast field production.

Excel base tool was developed for applying the surrogate model to forecast production for the group of well with have similar surface condition. This tool was tested by applying it to forecast field production for a group of 7 wells. The result shows that

production profile generated from the surrogate model has similar trend and its production forecast is slightly different from historical production data.

Applying Monte Carlo simulation technique to this tool could help user to identify the uncertainty in the gas production profile. And it would helpful for planning operation schedule in order to sustain production rate meet business target.

Surrogate models developed by this research can be applied for field that has similar properties only. Otherwise, it might create error in production prediction. So recommendation for the future work is to develop model in various reservoir properties in order to apply with more diverse reservoir properties and operating conditions.

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        Simulation Symposium</u>, Houston, Texas USA, Jan 31 – Feb 2

APPENDICES

APPENDIX A

Simulation model construction

Figure A.1 is simulation model build in GAP.
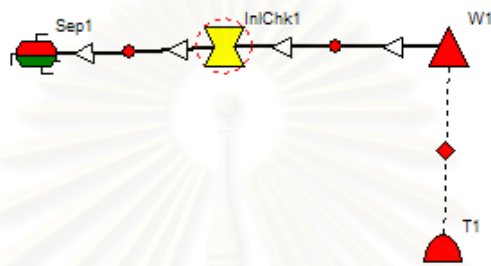
Figure A.1: GAP simulation model

This symbol refers to separator. But the separator in GAP does not have to be the physical separator in the field. It is simply a point of fixed pressure in the network.

This symbol refers to choke.

This symbol refers to reservoir section which linkable to MBAL. All material balance calculation was done here.

From MBAL required parameter was show in figure A.2 to A.5. Step of input was describe as follow

First is parameter input for PVT calculation.

Figure A.2: PVT input section in MBAL

Second is parameter input for Tank model.

Figure A.3: Tank input section in MBAL

Third is input parameter for aquifer model.

Figure A.4: Water influx input section in MBAL

Fourth is input parameter for relative permeability

Figure A.5: Relative permeability input section in MBAL

This symbol refers to well section which linkable to Prosper. The Inflow performance relationship and Vertical lift performance are calculated here.

From Prosper required parameter was show in figure A.6 to A.9. The step of input was describe as follow

First is input parameter for deviation survey section to identify shape of well.

Figure A.6: Deviation survey input section in Prosper

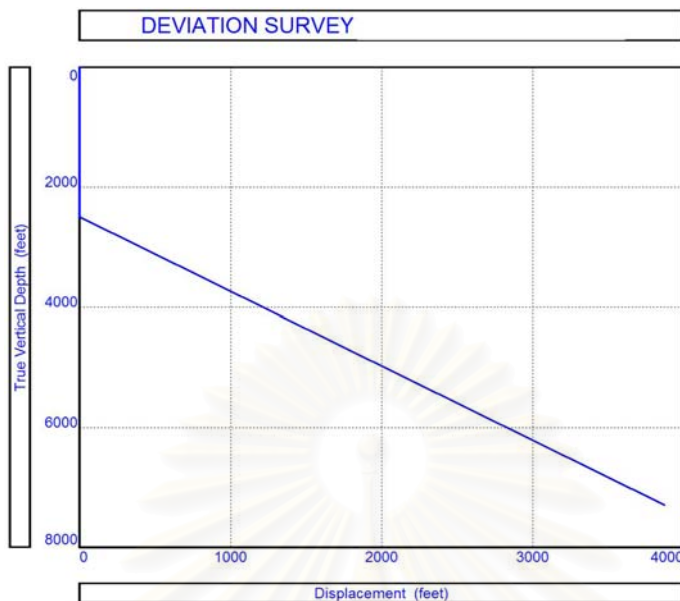And deviation survey also can plotted as shown in figure A.7

Figure A.7: Deviation survey plot

Second is input parameter for downhole equipment to identify restriction in well and tubing size diameter.

Figure A.8: Downhole equipment input section in Prosper

Third is input parameter for geothermal gradient calculation.

Figure A.9: Geothermal gradient input section in Prosper

After complete this input section, VLP can generated by vary some input variable to make it cover entire range of variable during running simulation.
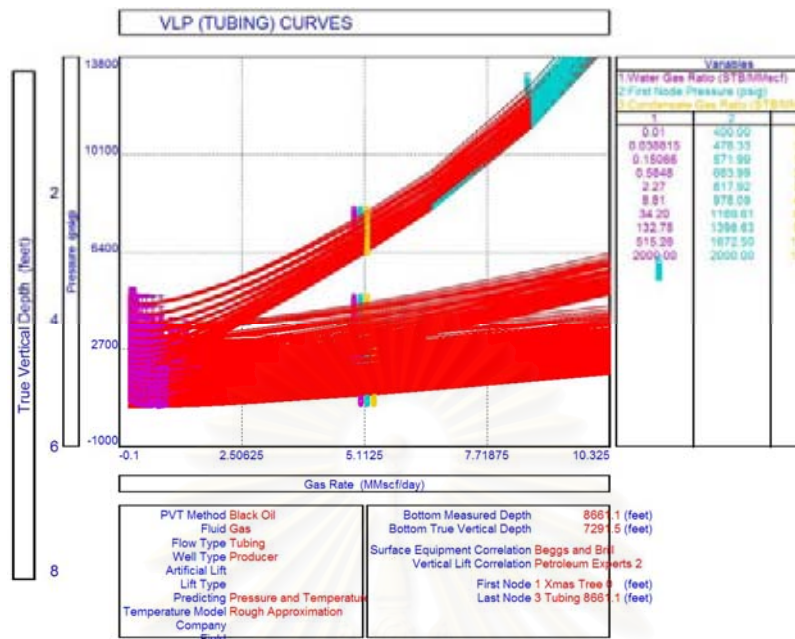
Figure A.10: VLP calculation

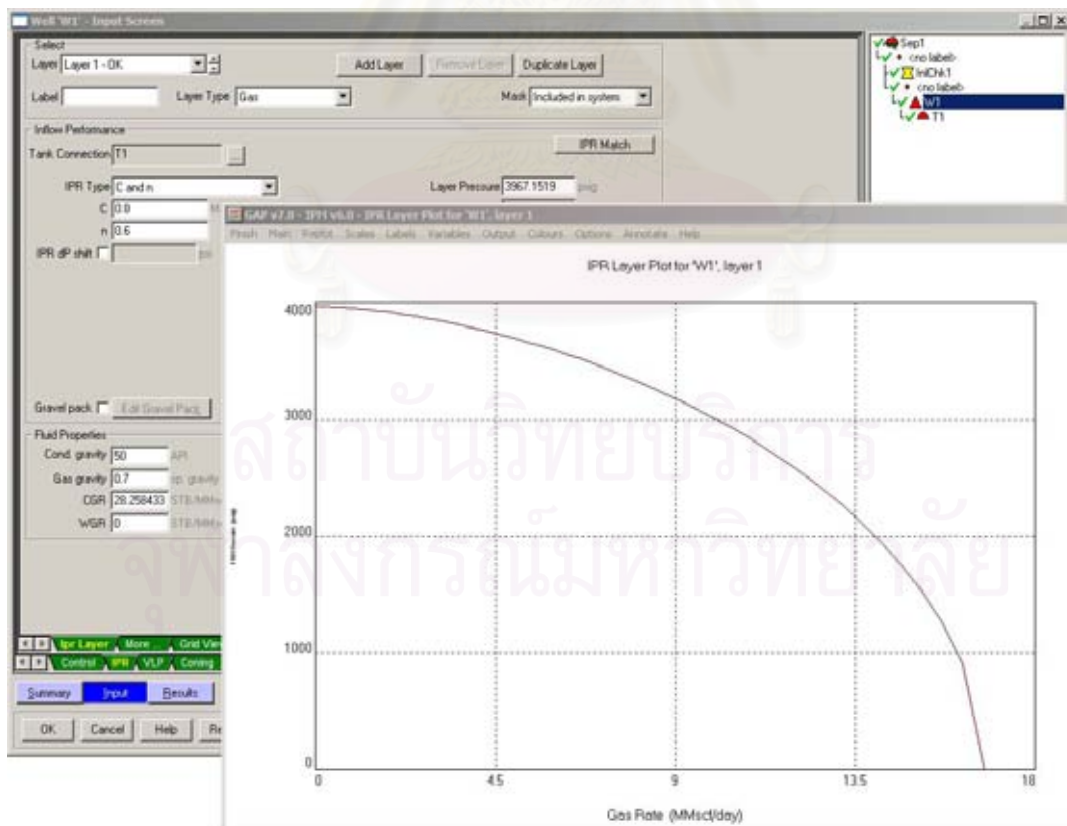Prosper also generate inflow performance relationship which can transfer to GAP in order to do the process.

Figure A.11: IPR calculation

APPENDIX B

Openserver template

```vba
Option Explicit
'Petroleum Experts Ltd - Open Server VBA Example

' These lines declare global variables
Dim Server As Object
Dim Connected As Integer
Dim lErr As Long
Dim Command As String
Dim AppName As String
Dim OSString As String
Dim typeFluide As Long


Sub Macro()

Connect

'Write Macro Here

Disconnect

End Sub

Sub Connect() 'This utility creates the OpenServer object which allows
'comunication between Excel and IPM tools

    If Connected = 0 Then
        Set Server = CreateObject("PX32.OpenServer.1")
        Connected = 1
    End If

End Sub
Sub Disconnect()

    If Connected = 1 Then
        Set Server = Nothing
        Connected = 0
    End If

End Sub
```

Figure B.1: OpenServer script template

```
'This utility function extracts the application name from the tag string
Function GetAppName(Strval As String) As String
    Dim Pos
    Pos = InStr(Strval, ".")
    If Pos < 2 Then
        MsgBox "Badly formed tag string"
        End
    End If
    GetAppName = Left(Strval, Pos - 1)
    If StrComp(GetAppName, "PROSPER", 1) <> 0 And StrComp(GetAppName, "MBA
        MsgBox "Unrecognised application name in tag string"
        End
    End If
End Function
```

```
' Perform a command, then check for errors
Sub DoCmd(Cmd As String)
    Dim lErr As Long
    lErr = Server.DoCommand(Cmd)
    If lErr > 0 Then
        MsgBox Server.GetErrorDescription(lErr)
        Set Server = Nothing
        End
    End If
End Sub
```

```
'Set a value, then check for errors
Sub DoSet(Sv As String, Val)
    Dim lErr As Long
    lErr = Server.SetValue(Sv, Val)
    AppName = GetAppName(Sv)
    lErr = Server.GetLastError(AppName)
    If lErr > 0 Then
        MsgBox Server.GetErrorDescription(lErr)
        Set Server = Nothing
        End
    End If
```

```
' Get a value, then check for errors
Function DoGet(Gv As String) As String
    Dim lErr As Long
    DoGet = Server.GetValue(Gv)
    AppName = GetAppName(Gv)
    lErr = Server.GetLastError(AppName)
    If lErr > 0 Then
        MsgBox Server.GetLastErrorMessage(AppName)
        Set Server = Nothing
        End
    End If
End Function
```

Figure B.1 (continued): OpenServer script template

```
' Perform a command, then wait for the command to exit
' Then check for errors
Sub DoSlowCmd(Cmd As String)
    Dim starttime As Single
    Dim endtime As Single
    Dim CurrentTime As Single
    Dim lErr As Long
    Dim bLoop As Boolean
    Dim step As Single

    step = 0.001
    AppName = GetAppName(Cmd)
    lErr = Server.DoCommandAsync(Cmd)
    If lErr > 0 Then
        MsgBox Server.GetErrorDescription(lErr)
        Disconnect
        End
    End If

    While Server.IsBusy(AppName) > 0
        If step < 2 Then
            step = step * 2
        End If
        starttime = Timer
        endtime = starttime + step
        Do
            CurrentTime = Timer
            'DoEvents
            bLoop = True
            Rem Check first for the case where we have gone over 1
            Rem and the number of seconds will go back to zero
            If CurrentTime < starttime Then
                bLoop = False
            Rem Now check for the 2 second pause finishing
            ElseIf CurrentTime > endtime Then
                bLoop = False
            End If
        Loop While bLoop
    Wend
    AppName = GetAppName(Cmd)
    lErr = Server.GetLastError(AppName)
    If lErr > 0 Then
        MsgBox Server.GetErrorDescription(lErr)
        Disconnect
        End
    End If
End Sub


' Perform a function in GAP, then retrieve return value
' Finally, check for errors
Function DoGAPFunc(Gv As String) As String
    DoSlowCmd Gv
    DoGAPFunc = DoGet("GAP.LASTCMDRET")
```

Figure B.1 (continued): OpenServer script template

```
    lErr = Server.GetLastError("GAP")
    If lErr > 0 Then
        MsgBox Server.GetErrorDescription(lErr)
        End
    End If
End Function
```

Figure B.1 (continued): OpenServer script template

VITAE

Piyanai Klinnoi was born on September 24, 1981 in Phitsanuloke, Thailand. He received his B. Eng. in Naval Architecture and Marine Engineering from the Faculty of Engineering, Chulalongkorn University in 2003. After graduating, he continued his study in the Master of Petroleum Engineering program at the Department of Mining and Petroleum Engineering, Faculty of Engineering, Chulalongkorn University.