Modified Data Envelopment Analysis of Multiple Response Experiments in the Robust Parameter Design Procedures

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ABSTRACT

Selecting the optimum process parameter level setting for multi-quality processes is cumbersome. Robust parameter designs procedure that utilizes different strategies for improving performance/productivity during product and process design so that quality response can be obtained efficiently and optimally. An inevitable problem that is associated with the product and process design is in appropriating process variables that will yield optimal response. The complexity of the problem is peculiar with multiple response experiments (processes) where different factor level combinations yield varying responses. Previous methods are plagued with complex computational search, unrealistic assumptions, ignoring the interrelationship between responses and failure to select optimum process parameter level setting. This thesis proposes the implementation of modified variable return to scale (VRS) data envelopment analysis in the Robust Parameter Design (RPD) procedures to estimate and optimize responses of all non-dominated (significant) factors level combinations in multi-response experiments. This study also enhances the discriminatory tendency of the model by imposing VRS partitioning within the model.

The model is conducted in a manner that with an adequate BPNN topology, experiment with incomplete, missing or censored data whenever encountered, could be investigated. Here, standard DEA modes are allowed to self-assess, the upper bound is restricted and the VRS penalization coefficient is adopted to determine the optimum process parameter level setting. The proposed procedures are applied to seven different case studies and the results were compared with existing methods of principal component analysis (PCA), DEA based ranking approach (DEAR), genetic algorithm (GA), grey relational analysis (GRA) and benevolent formulation (BF). The effectiveness of the proposed model measured by the total anticipated improvement yielded the highest total improvement over the existing methods. In overall, many inefficient DMUs that would have been promoted as efficient by the standard DEA models were revealed. The discriminative tendency further gives insight to DMUs that are within the convex set of the factor level settings and those that are not, thereby making the computation search for the optimal easy and simple.

Keywords: VRS modified and penalization coefficient, robust parameter optimization, DEA discrimination, integrated exergetic-data envelopment analysis, multi-response robust parameter procedures

ÖZ

Çok kaliteli işlemler için optimum işlem parametre seviyesi ayarının seçilmesi zahmetlidir. Ürün ve süreç tasarımı sırasında performans / üretkenliği arttırmak için farklı stratejilerden yararlanan sağlam parametre tasarımları prosedürü, böylece kalite yanıtının verimli ve optimal bir şekilde elde edilebilmesi için. Ürün ve süreç tasarımı ile ilişkilendirilen kaçınılmaz bir sorun, optimal yanıtı sağlayacak süreç değişkenlerini kullanmaktır. Problemin karmaşıklığı, farklı faktör seviyesi kombinasyonlarının değişken tepkiler verdiği çoklu cevap deneyleri (süreçleri) ile özeldir. Önceki yöntemler, karmaşık hesaplamalı arama, gerçekçi olmayan varsayımlar, yanıtlar arasındaki ilişkiyi görmezden gelmek ve optimum işlem parametresi seviyesi ayarını seçememekle boğuşmaktadır. Bu tez, çoklu yanıt deneylerinde, baskın olmayan (önemli) faktörler düzeyindeki tüm kombinasyonların yanıtlarını tahmin etmek ve optimize etmek için Sağlam Parametre Tasarımı (RPD) prosedürlerinde, ölçek değiştirmeli (VRS) veri zarflama analizine modifiye değişken getirisinin uygulanmasını önermektedir. Bu çalışma aynı zamanda modelde VRS bölümlendirmesi uygulayarak güçlü parametre prosedüründe modifiye değişken dönüş ölçeğine (VRS) modelin ayrımcı eğilimlerini de arttırmaktadır.

Model, yeterli bir BPNN topolojisi ile, karşılaşılan eksik, eksik veya sansürlenmiş verilerle deneylerin araştırılabileceği bir şekilde gerçekleştirilmiştir. Burada, standart DEA modlarının kendi kendini değerlendirmelerine izin verilir, üst sınır kısıtlanır ve optimum işlem parametre seviyesi ayarını belirlemek için VRS cezalandırma katsayısı benimsenir. Önerilen prosedürler literatürden yedi (7) farklı vaka çalışmasına uygulanmış ve sonuçlar, temel bileşen analizi (PCA), DEA tabanlı

sıralama yaklaşımı (DEAR), genetik algoritma (GA), gri ilişkisel analiz (GRA) ile karşılaştırılmıştır.) ve yardımsever formülasyon (BF). Önerilen modelin beklenen toplam iyileşme ile ölçülen etkinliği, mevcut yöntemler üzerinde en yüksek toplam iyileşme sağlamıştır. Genel olarak, standart DEA modelleri tarafından verimli olarak tanıtılacak çok sayıda verimsiz DMU ortaya çıkar. Daha da ilginç olarak, faktör seviyesi ayarlarının dışbükey kümesi içinde bulunan ve aramada dikkate alınmaması gereken DMU'lara içgörü sağlayan ayırt edici eğilim, hesaplama raporunu diğer rapor edilen yöntemlere kıyasla kolay ve basit hale getirmektedir.

Anahtar Kelimeler: değiştirilmiş VRS ve cezalandırma katsayısı, gürbüz parametre optimizasyonu, DEA ayrımcılığı, ekserjetik yıkım dağılım eğrisi, entegre ekserjetik veri zarfı analizi, çoklu yanıt gürbüz parametre prosedürleri

I dedicate this work to The Almighty God

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I will always praise you, my Lord and my God, I worship your name, for you changed not… "Unto Him who is able to do exceeding abundantly above all what I ask or think, according to the power that worketh in us. For every good gift and every perfect gift is from above, and cometh down from the Father of lights, with whom there is no variableness, neither shadow of turning. Of His own will begat me with the word of truth, that I should be a kind of firstfruits of His creations."

Unto Him be glory in the Church by Christ Jesus throughout all ages, world without end. Amen.

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"I pledge to Nigeria my country, to be faithful, loyal and honest. To serve Nigeria with all my strength, to defend her unity, and uphold her honour and glory, so help me God."

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INTRODUCTION

1.1 Background of Study

The old, online traditional methods of quality assurance are based solely and primarily on inspecting products as they are discharged from the production line and rejecting those products that fail to meet up with the specified acceptance range. However, it has been pointed out that no amount of inspection can improve the product's quality attributes and that quality must be built into the product right from conception (Taguchi et al., 2005). Robust parameter design is an engineering procedure that utilizes different strategies for improving performance during product and process design so that quality response can be obtained efficiently and optimally. This off-line quality control procedure idea stemmed up due to the need to enhance the dependability of controllable factors to the effects of the variations in the uncontrollable factors so that the overall quality response is insensitive to the effects of the variations (Taguchi et al., 2005; Al-Refaie and Al-Tahat, 2011). It involves experimental design using orthogonal arrays techniques to determine optimal factor level combinations for a specified efficiency or performance of quality indicators, usually signal-to-noise (SN) ratio. However, the robust parameter could not be used to attain optimum factor level combination that will maximize the multi-response objective. Liao (2004) described the Taguchi method as an efficient method used in off-line quality control in that the experiment design technique is combined with the quality loss. However, Wysk et al. (2000) informed that Taguchi was quick to point out that no amount of inspection can improve a product and that quality must be designed into a product right from conception.

Taguchi method has been used to improve quality through finding the optimal controllable factor combination (parameter factors) that will reduce the effects of variations due to the presence of the uncontrollable factor (noise factors) at both process and product design stage. Both parameter and noise factors are the input while the specified quality target serves as the response. It was found by Al-Refaie and Al-Tahat (2011) that one major problem of the Taguchi method ever identified was its inability to effectively and efficiently optimize multiple response problems. Taguchi method has been successful in its applications to single response experiments. In the real world and in reality, more than one quality target is necessary for most processes and industrial application even as customers' quality concerns and utility for consuming a product are usually more than one and thus given rise to multiple response problems. Attempts have been made by various researchers to solve this problem and a robust parameter design has been achieved through the use of data envelopment analysis (DEA) and artificial neural network (ANN) within the Taguchi procedures. However due to the failure of these attempt vis-a-vis the weak DEA model used. Also the ANN topology used in their various solutions was not selected by training and cross validation and thus the level of the uncertainty could not be adequately ascertained. Therefore there is the need to carry out further studies on to better solve the menace of classical DEA models in order to enhance the solution to the multi-response experiments in the robust parameter procedures domain. The purpose of the ANN in the proposed model of this study is to ensure that the model is versatile, viable and applicable to solve multiple response problems in the robust parameter procedures, in all situations, especially when censured or missing data is encountered. With the inclusion of how to train, validate and select an adequate ANN, the proposed model is saved from being redundant in the presence of missing data.

1.2 Concept of Robust Parameter Design

Many companies have also discovered that the traditional techniques of quality control were not competitive with the Japanese quality control methods that have been in use since the 1940s. Traditional quality control methods are based strongly and solely upon inspecting products during production line and rejecting those products that fail certain acceptance or quality parameters or ranges. Taguchi method allows for improvement in the consistency of production output and performance irrespective of the environment in which it is carried out. Taguchi design noted that no amount of inspection can improve a product because not all factors that cause variability can be controlled. Therefore quality must be designed into the product from conception.

Factors are classified into two distinct classes of those that are controllable and those are uncontrollable (noise). Taguchi therefore aimed at identifying optimum controllable factor settings (level combination) that minimize process variability. There is the need to understand these classes of process factors. Controllable factors (design or control factors) are those factors that can be easily moderated, adjusted or controlled by the designer. These are not limited to material choice, cycle time, or operating temperature, process route choice, and type of catalysts used, choice of the condition. Uncontrollable factors (noise factors) could be described as forces compelling or causing deviations from production or quality target. It can be subdivided into three types namely external, internal, and unit-to-unit noise factors.

External noise factors are those that arose due to the exposure or variation in the condition of use. Internal noise factors are due to production variations while unit-to-unit are as a result of deterioration or variation with time of use. Noise factors are difficult or almost impossible to control and could be expensive when attempted to control or eliminate them. Due to the foregoing, it is rather pertinent to render their effects null and void or better still, insignificant or insensitive to the quality output instead of eliminating them completely. In other words, noise factors are still within the system but properly and optimally selected controllable factor/level combination will be least sensitive to their presence and their effects.

1.3 Taguchi Optimization Techniques

Taguchi method sees, understands and treats quality control optimization problems as either static or dynamic problems. Static Taguchi Optimization Problems which could also be referred to as batch process optimization involves a process where several factors directly dictate the value of the target output (value of the quality attributes sought for). For the static problem, optimization will only be based on how to select the optimum control factor/level combination that will yield the output at the set target. This can be depicted in the Figures 1;

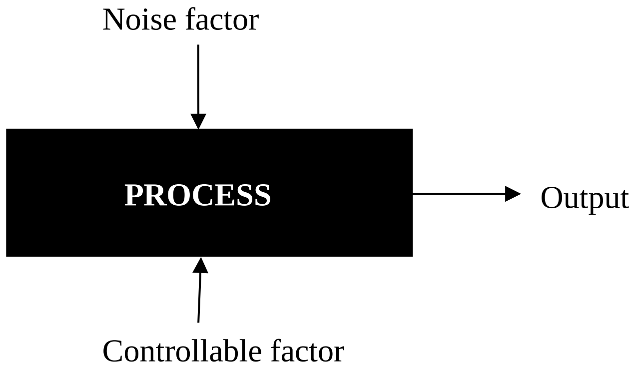


Figure 1. “Black” box depicting the Taguchi robust modeling of static problem

Dynamic Taguchi optimization problem, on the other hand, could be thought of as a system proposed, having a signal input such that a particular signal input directly determines the value closest to the set target for the output. The major aim of the optimization will be to achieve optimum factor/level combination such that the rate of the input signal to the output signal is closest to the set output. This can also be illustrated in the Figure 2;

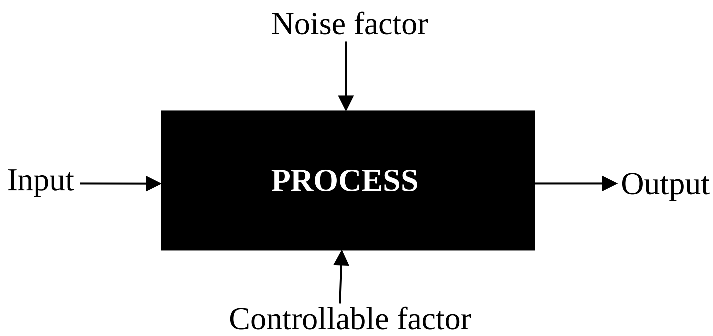


Figure 2. “Black” box depicting the Taguchi robust modeling of dynamic problem

Taguchi proposed three steps technique for developing good quality products and processes. These are system design, parameter design and tolerance design. An experiment must be carried out to implement parameter and tolerance designs.

1.3.1 System design

System designs involve creating ideas on what to experiment. It is a conceptualization step where the aims of the research or experiment have identified the variables (factors) and response(s). Identification and classification of variables into controllable and noise factors are also done.

1.3.2 Parameter design

This can be done after the system design concepts are successfully set out. Control and noise factors values or levels are set. Controllable factor/level combinations that give most insensitivity to the noise factors are evaluated and selected. It has been referred to as the utilization of nonlinearity or utilization of interaction between control and noise factors. Parameter design is a two-step optimization approach with the first step in determining the combination of parameter levels that are competent enough to render the influences of the noise from noise sources. The second step involves the enhancement of the robustness of the product by setting the appropriate target through the selection of a control factor whose level change affects the average and at the same time affecting variability minimally. This two-step differentiates robust parameter design from the conventional design of experiment (DoE). In DoE, the first step will be to try to achieve the target before the variability is dealt with. In the real world, experimental results and some analytical technique have been used for the parameter design. This is the most important step toward developing state and reliable manufacturing process that will lead to quality products and quality-controlling countermeasures are achieved in this design.

1.3.3 Tolerance design

Similarly, when the results of the parameter design are concluded successfully, an effort can now be made to focus on the reduction and minimization of the variation in the quality attributes. Here consideration is given to the process environmental conditions and the system components. These are considered as noise factors and are structured in orthogonal arrays in order to determine the extent of their influence on the responses. This involves the use of Orthogonal Array (OA). OA is so significant in the sense that it allows possible factor combinations to occur at equal time in a two columns experiment. Simpson et al. (2000) described Orthogonal Arrays (OA) as a tool that is specifically employed in Taguchi's approach to systematically vary and test different levels of each of the control factor.

Orthogonal Array columns are arranged as inner and outer arrays. The inner array consists of the controllable factors while the outer array consists of the noise factor. Most often, the inner array is usually orthogonal in design. Simpson et al. (2000) opined that inner array consists of the OA that contains the control factor settings while the outer array consists of the OA that contains the noise factors and their settings which are under investigation. They further concluded that the combination of the "inner array" and "outer array" constitutes what is called the "product array" or "complete parameter design layout. At this level, factors level combinations that can provide the optimal response will be generated. This is achieved by the evaluation of the quality loss function where appropriate Signal-to-Noise ratio (SN) quality indicators are selected. This can either be Smaller-The-Better (STB), Larger-The-Better (LTB) and Nominal-The-Better (NTB) or it can be paired or the three used in combination depending on the type of response anticipated in the experiment.

1.3.4 Robust Parameter design

Robust parameter design is an engineering procedure that utilizes different strategies for improving performance during product and process design so that quality response can be obtained efficiently and optimally. Similarly, Martin and Ida (2008), robust design methodology means systematic efforts to achieve insensitivity to noise factors. It is worthy to note that the application of Taguchi method inculcates quality control measures at both the product and process design stages to improve product manufacturability and reliability by making products insensitive to environmental influences and component variations. The end result is a robust design which is a design that has the minimum sensitivity to variations in uncontrollable factors.

1.4 Data Envelopment Analysis

In general, DEA has been referred to as a fractional mathematical programming technique solely responsible for evaluating the efficiency or performance of homogeneous decision-making units (DMU) with multiple inputs and outputs system. Rocha et al. (2016) described data envelopment analysis (DEA) as a linear programming technique used for determining the relative performance of a set of competing DMUs whenever multiple inputs and outputs make the comparison cumbersome. It is a non-parametric technique for measuring technical efficiency of various systems. By technical efficiency, we mean the degree of industry technology level that the production process of a production unit reaches. This can be determined from two perspectives (i) input and (ii) output. From input aspect under the input condition defined for the system, the technical efficiency is measured by the degree of output maximization and for output perspective under the output condition defined; the technical efficiency is measured by input minimization. In both cases, technical efficiency can be estimated quantitatively as a ratio of output to input.

Wu et al. (2009) narrated that since its initial proposition, a constant return to scale assumption model CCR coined after the first letter of the first name of the proposers have been used to determine the efficiency of many systems. The model according to Al-Refaie (2012) measures the technical efficiency of individual DMU relative to other DMUs with the same inputs and outputs. CCR model assumes that all appraised DMUs are at the optimal production scale stage, a stage of constant returns to scale even though the returns to scale of production technology varies. This is not true for real practical production since many production units are not likely to be in the constant scale of production. Hence the technical efficiency of the CCR model includes some component of the scale efficiency. The proposed second DEA model as reported in Ma et al. (2014) Variable Return to Scale (VRS) assumption model, also referred to as BBC coined from the first letter of the first name of the proposers, accounted for the component of scale efficiency thereby making it easy for processes examined in regions of increasing, constant and decreasing return to scale. CCR model can determine CCR efficiency in both primal and dual modes. In summary, DEA models see the production possibility set (PPS) as convex. This implies that all of the points on the line of the segment that connect any two DMUs belong to the PPS.

1.5 Artificial Neural Network

The two main reasons for using neural networks for this task instead of other classical estimation such as regression analysis are their non-parametric character and their generalization capability. Thus, on one hand, neural networks can approximate without making any prior assumption, any existing linear or nonlinear mapping between the control variables and Signal-to-Noise ratios. On the other hand, well-trained neural networks are able to estimate, with acceptable error levels, the output values for any control variable combination, not just the ones experimentally tested. Among the several conventional supervised learning neural networks are the perception, back propagation neural network (BPNN), learning vector quantization (LVQ), and counter propagation network (CPN). The BPNN model is employed due to its ability to achieve effective solutions for various industrial applications and its power in the modeling of a nonlinear and complex relationship between systems input and output. Thus the number of input neurons equals the number of control variables; the output layer has one neuron corresponding to the response anticipated.

1.6 Statement of Problem

Taguchi robust parameter design method has been widely used to improve quality through the reduction of the effect of uncontrollable factors (noise factors) on the quality response both at the process and product design stages. However, one of the major problems of the Taguchi method was its inability to effectively and efficiently optimize processes with multi-quality response (Al-Rafaie and Al-Tahat, 2011). Several attempts, which have been made to solve this problem, ended up complicating the problem (Al-Rafaie, 2011, 2012; Liao, 2002). In reality, these previously adopted techniques are too cumbersome to be comprehended and applied by many decision makers. More so, most of these methods assumed that the variance between responses is constant throughout thereby snubbing the dispersal effect of those multi-quality responses.

Similarly, reports of previous works established that standard DEA models (CCR and VRS) are weak. This weakness is an intrinsic menace within the VRS models is the tendency of the model to assign misleading efficiency scores thereby promoting DMUs with a pseudo weighing scheme as an efficient DMU. These weaknesses of the standard VRS model are (a) inability to offer scale (pure) technical efficiency (b) tendency to assign misleading scores to an inefficient units (c) efficiency score at input orientation is the same with the efficiency score at output orientation. It will be noted that all the ranking approaches were used to cope with the weakness of the standard CCR DEA model. Their efforts were only geared toward removing the inability of the standard CCR model to produce scale (pure) technical efficiency but weaknesses (b) and (c) were not thoroughly dealt with. Adler et al. (2002) after a thorough review and application of some of the proposed ranking methods concluded that no one of them could be prescribed as an adequate solution to fully rank the DMUs in the DEA approach. This research used VRS (VRS) model because scale (pure) efficiency can be achieved by its application and the fact that weakness (c) does not occur with VRS model making it a veritable basis for partitioning and provide the leverage for the DMUs to self-assess to estimate the restriction for the upper bound of the free variable.

The problems with the previous DEA integrated applications are mostly in the use of standard DEA models (CCR and BCC) and their inability to select adequate ANN topology in their procedures. Most of these methods could not select the optimum process parameter level setting. This study seeks to enhance the robustness of the application of DEA integrated model in the robust parameter design by increasing the discrimination among DMUs through the application of the modified VRS to remove the menace of VRS model by restricting the upper bound of the free variable u_0, incorporate BPNN topology with adequate numbers of neurons at the hidden layer into the modified VRS model to optimize and select adequate process parameter level setting using the VRS penalization coefficient. In the proposed model, assumptions are drastically reduced, the inputs and outputs are allowed to self-assess to produce their weights, computations are simplified, and the procedure is completely non-parametric ensuring its accuracy and its simplicity for quality engineers and managers to understand and implement.

1.7 Objectives of Study

The specific objectives of this study are;

(a) to revamp and use the modified DEA (facet analysis) for optimizing and selecting optimum factor level setting for multi-response experiments in the robust parameter design by imposing VRS partitioning and select the optimum factor level combination,

(b) to verify the effectiveness of the proposed model over the known and widely reported models,

(c) to apply the revamped modified VRS-robust parameter procedures to exergetic analysis and other processes.

1.8 Analysis of the technique

This robust parameter procedure is achieved in four phases: data collection and generation, responses evaluation using the artificial neural network, efficiency determination using modified DEA, optimization to determine and select optimum factor level combination.

Phase A (Data generation and collection)

The major aim of this phase is to gather data for signal-to-noise ratio estimation using the orthogonal array, for neural network training for factor level combination and response prediction as the case may be. This phase consists of five steps:

Step 1 (identifying controllable factors).

In this phase, process operating parameters are determined. This leads the identifying design/control factors and the noise factors. Effort is made to identify significant factors amongst selected design and noise factors.

Step 2 (selecting adequate orthogonal array). After significant factors have been selected, various levels for each factor were suggested. This suggestion was only for an experiment that is fixed effect in nature.

Step 3 (Conducting the experiment and literature data). After setting up the orthogonal array, the actual experiment is conducted to generate various inputs and outputs (responses) data are determined.

Step 4 (estimation signal-to-noise ratios for responses from experimental data).

For the experiment, their respective signal-to-noise ratio is predicted using an adequately trained ANN topology. The three quality loss functions of response used are those suggested according to the Taguchi method are the nominal-the-better (NTB), smaller-the-better (STB) and larget-the-better (LTB).

Step 5 (Normalized signal-to-noise-ratio estimation NSNs)

The normalized signal-to-noise-ratio (NSNs) values are estimated. Normalization of SN ratios converts the different units of the responses into dimensionless numbers. Salmasnia, Bastan, and Moeini (2012) gave the limit of the NSNs estimated as from a minimum of zero to a maximum of one ($0 \leq NSNi\ j \leq 1$).

Phase B (Data prediction using BP-NN). This phase becomes necessary when all the data needed for the experiment could not be obtained from the experiment carried or as mentioned BP-NN neural network was used to predict the values other control factors levels combinations beyond the experimented data and their corresponding NSN. This phase is achieved in three steps as follow:

Step 1 (neural network topology and architecture selection). The BPNN model is employed due to its ability to achieve effective solutions for various industrial applications and neural networks power in the modeling of a nonlinear and complex relationship between systems input and output.

Step 2 (selection of the training and the testing data). An adequate BPNN topology and architecture was trained, tested and validated using the actual experimental data.

Step 3 (factor levels and corresponding signal-to-noise ratio prediction). A well trained, tested and validated BPNN topology and architecture was used to predict the SN ratios for all possible control factor levels combinations.

Phase C (determination of the efficiency of DMUs using modified DEA). Facet analysis was used to evaluate the efficiency frontier of each factor level combination.

Phase D Optimization to select optimum DMU

To optimize and select optimum DMU, penalization coefficient of the efficient DMUs obtained at Phase C above is estimated. Based on the highest value of the penalization coefficient, the optimum system is selected.

Seven case studies are examined altogether to demonstrate the effectiveness of the model over the existing models; out of which two case studies food fermentation and exergetic analysis is examined to further illustrate how the proposed model can be adopted for new concepts. These case studies are hard disk drive operation, gear hobbling operation, rhamnolipid production, apple dehydration, bio-fermentation experiment for the production of "Burkutu", a local Nigerian alcoholic beer and, exergy analysis and simulation of multicomponent carried out to integrate the proposed model into exergetic analysis and supplier selection in supply chain management.

Chapter 2

LITERATURE REVIEW

2.1 Previous models proposed for solving multiple response problem of Taguchi robust parameter design

These methods can be categorized into those that did not integrate DEA into their models, those that employed the classical Design of experiment models and those that used DEA integrated model.

2.1.1 Previous non DEA integrated models

The method of assigning weight as used by Lin and Lin (2002) was plagued with the difficulty of how to describe and evaluate weights for responses in a real case. The proposed method of regression further complicated the computational process by failing to establish vividly the correlations among the responses. This was evidently revealed by the larger means square error (MSE). Liao 2004 reported that the method of principal component analysis (PCA) has the shortcoming of how to trade-off to select feasible solution whenever more than one eigenvalue comes out to be greater than 1. This situation results in the multi-response losing their optimization directions when analyzed within the robust parameter strategy.

Furthermore, PCA is based on the strict assumption that the residual errors of the variables are randomly multivariate normally distributed (Al-Refaie, 2011). Salmasnia et al. (2012a) tried to solve the PCA menace by incorporating desirability function (DF) and ANFIS, an AI tool but this could not account for the relative significance of responses during optimization as it only achieved the reduction in the pair of the efficient system (Adler and Golany, 2001). Gomes et al. (2013) further attempted to improve on the identified drawbacks of PCA with a study using weighted multivariate MSE (WMMSE) integrated with PCA and response surface methodology (RSM) for process optimization. Their study obtained the uncorrelated weighted object functions using the original responses and optimized these functions with the help of the optimization algorithms. The efforts confirmed the selection of the optimum parameter setting with the illustrated case study. PCA, genetic algorithm (GA), desirability function (DF), grey relational analysis (GRA), exponential desirability function (EDF), simulated annealing (SA) and multiple adaptive neuro-fuzzy inference systems (MANFIS) have been used in the robust optimization (See, Noorossama et al., 2009; Chang, 2008; Chang and Chen, 2011; Sibalija et al, 2011, Salmasnia et al., 2012a). In reality, these techniques are too cumbersome to be comprehended and applied by many decision makers. More so, most of these methods assumed that the variance between responses is constant throughout thereby snubbing the dispersal effect of those multi-quality responses.

2.1.2 Classical Design of Experiment (DoE) methods

Fundamentally, Taguchi robust parameter design is hinged on the DoE methods, and since over two decades efforts have been geared toward the development of alternatives and improvements of the procedures of Taguchi robust design. Suitable classical experimental design approaches will be exposed comparatively to robust parameter design. The most common classical DoE is the response surface methodology (RSM). The dual response model formally proposed by Vining and Myers (1990) fitted for the mean and the variance requires the inner-outer arrays type of a replicated experiments. The single response of Welch et al. (1990) allowed the control factors and the noise factors to coexist within the same model. Steinberg and Bursztyn (1998) analyzed both single and dual response model and concluded that the single model has higher propensity than the dual only if the noise factors have been controlled with a fixed model or level experiments. Shoemaker et al. (1991) implemented the classical DoE (RSM) by including the noise factors and the control factors in the matrix and opined that the model could result in cost-efficient experiments. Sequel to this, a mixed resolution RSM model of Lucas (1989; 1994) was implemented with high resolution for the control-noise factor interactions and for control-control interactions with lower resolution for noise-noise interactions, and came out that a mixed resolution RSM model has superiority over the experimental designs as implemented by Taguchi robust parameter design (Borkowski and Lucas, 1997).

The Split-plot DoE model which allows incompletely randomized experimental order, where factors are disallowed to reset between each experiment was proposed by Box and Jones (1992), Letsinger et al. (1996) and Bisgaard (2000) was said to permit a precise determination of the control-noise factor interactions. This has been corroborated with similar recent studies of Kowalski (2002), Leoppky et al. (2002), Bingham and Sitter (2001; 2003), and McLeod and Brewstar (2006). Further studies on the application of various RSM techniques Aggarwal et al. (2007), Benyounis and Olabi (2008), Robinson et al. (2003) and Myer et al. (2004) revealed that design of experiment (DoE) is indeed useful for robust design and finally concluded that Taguchi robust parameter design is time-efficient and effective and could greatly improve product quality and reliability at low costs. Approaches such as the central composite design (CCD) of RSM (see Montgomery, 2009 for more explanation of this concept) as applied in the work of Brito et al. (2014) used MSE and reported that it offered reduced sensitivity of the effect of process variability. It will be recalled that some efforts of Luzano and Gutierrez (2010) and Wu and Chyu, 2002 reported that signal-to-noise ratio (SN) has been expressed as a function MSE (with both SN and quality loss said to be related to MSE. An integrated RSM-Generalized linear model (GLM) proposed by Lee and Nelder (2003) short-lived because the assumptions made in RSM could not justified, Eugel and Huele (1996) GLM where the residual variance cannot be assumed was proposed and Myers et al. (2005) suggested GLM with non-normal responses.

In another related study of Rivero and Garcia (2001) parametric model was used concluded that parametric procedures could not adequately smoothen the uncertainties or variations in the system. Studies conducted by Arvidsson and Gremyr (2008) and Rao et al. (2008) to identify conflicts on the principles of robust design reported a wide range of agreements on the use of Taguchi robust parameter design and its contribution in emphasizing insensitivity of the control factor level combination to noise factors. This has created several industrial interests and applications of the method. Taguchi robust design principally aims at making the response of the process insensitive to the effects of variations while DoE or RSM usually aim at removing or eliminating these effects by reaching a compromise that will make up for the noise effect within the process. Effects from these noise factors are forces compelling or causing deviations from the quality target and they can be categorized into three namely external, internal and unit-to-unit noise factors. External noise factors are those that arise due to the exposure or variation in the condition of use. Internal noise factors are due to production variations while unit-to-unit are as a result of deterioration or variation with time of use. Arvidsson and Gremyr (2008) reported that Taguchi robust design has the capability to deal with all these categories of noise factors simultaneously unlike DoE techniques which most often can only deal with the unit-to-unit type.

Conclusively, as related to the use of the classical DoE approaches, it should emphasized in addition to the aforementioned superiority of Taguchi over the classical DoE that those reviewed DoE concepts are all based on explicit modelling of the responses and categorically aimed at increasing the understanding of the problem under study (understanding oriented). On the other hand, Taguchi robust parameter design is capable of both the understanding oriented as well as providing solution (solution oriented). Studies about the difference between Taguchi and statistical DoE approaches carried out by Lin et al. (1990) concluded that while DoE statistical methods provide what happened (how the problem happened – problem characterization) Taguchi robust parameter provides what or how make it happen (both problem characterization and solution or prevention). Therefore, a non-parametric data envelopment-robust parameter design methodology has been poised to be able to handle variations due to noise factors which most often can only deal with the unit-to-unit type. A non-parametric data envelopment-robust parameter design methodology has been poised to be able to handle variations due to noise factors.

2.1.3 Previously proposed integrated DEA model

Amongst existing methods, those that implemented DEA and artificial neural network (ANN) within the robust parameter design are of interest to this study. Many ranking techniques have been proposed to completely rank DMUs. Cross-efficiency through cross-evaluation matrix technique was introduced by Sexon et al. (1986), to cope with fully ranking of the DMUs with either aggressive (AF) or benevolent formulations (BF) has the major shortcoming of it evaluation losing its relationship with the weights of the input and output variables. Al-Rafaie and Al-Tahat (2011) showed that although BF achieved elimination of unrealistic weights problems of DEA model and midwifed a definitive ordering of DMUs, it is plagued by the use of average cross efficiency which does not offer Pareto results. Other efforts such as DEA game where all DMUs are seen as active competitors with the same chance has been put forward to tackle this problem where ultimate cross efficiency is used as ranking basis. Super-efficiency method as proposed by Andersen and Peterson (1993) has the following shortcomings; (i) objective function is regarded as the ranked position for the DMUs without minding the fact that each system is assigned different weight (ii) the presence of infeasibility evidently shows that the system did not attain a fully ranking status (See Zhu (1996a), Dula and Hickman (1997) and Seiford and Zhu (1999)), and (iii) the tendency of the super-efficiency to assign unusually high score to the specialized DMU. Similarly, the Benchmark ranking approach of Torgersen et al. (1996) has the problem of giving different conclusions as a result of an outlier where a choice DMU is always highly ranked and, consequently many DMUs are ranked with the same score.

Multivariate statistical approaches of canonical correlation analysis (CCA), linear discriminant analysis (DDEA) and discriminant analysis of ratios (DR/DEA) have been used to fully rank the DMUs. According to the report given by Adler et al. (2002), the application of CCA revealed that the results obtained are statistically significantly close; nonetheless, its ranking is only realistic when the weights gotten are positive. DDEA as applicable using the traditional discriminant analysis only gave results that are statistically close to that of standard CCR model. The implication is that some of the efficient DMUs may be ranked lower than the inefficient DMUs or vice-versa. The DR/DEA approach attempted to correct the infeasibility issues that have been found with CCA and DDEA is equally floored the inability to handle negative weights without incorporating another optimization model and even though this is done, there is still no assurance that the solution so obtained will be a global optimal.

An integrated DEA-robust design procedure of Liao (2004) to find an adequate solution to the existing problems of Taguchi robust involving censored or missing data using CCR model and a supervised learning multi-layer perceptron (MLP) BP-ANN model could only found significant and non-significant controllable factors and did not select the optimum factor level setting that will maximize the multi-response objective and thus the engineer is left with the choice of using his judgment in the selection. Luzano and Gutierrez (2010) attempted to solve the problems by incorporating BPNN in DEA to determine the mean response of the different parameter level settings. Therefore a three-step approach using a neural network with the VRS, non-radial score DEA model was presented to solve the problem of how to select the optimum factor level setting through robust quality loss penalization.
The gain of the technique was that it achieved the selection of the optimum factors level setting by using BCC (VRS) model and the use of the penalization coefficient nevertheless it did not deal with the identified menace of the VRS model identified in weakness (c) (see, e.g., Luzano and Gutierrez [2010, 1139-1148] on this concept).. Also, BPNN topology with the adequate number of neuron within the hidden layer was not achieved and this is capable of increasing the uncertainty associated with the use of BPNN and consequently hampering the robustness of the VRS model. Another issue is that their method allowed the upper bound of the free variable of the VRS model to be free and take any value between to; this is capable of introducing vagueness into their model. Therefore, our study attempts to solve this problem by

imposing VRS partitioning within the modified VRS model and also determine the number of neuron at the hidden layer of the BPNN in order to reduce the uncertainty associated with the application of BPNN.

2.2 The basis for the enhanced model approach

It will be noted that all the mentioned ranking approaches were used to cope with the weakness of the standard CCR DEA model. Their efforts were only geared toward removing the inability of the standard CCR model to produce scale (pure) technical efficiency but weaknesses (b) and (c) was not thoroughly dealt with. Adler et al. (2002) after a thorough review and application of some of the proposed ranking methods concluded that no one of them could be prescribed as an adequate solution to fully rank the DMUs in the DEA approach. This research used VRS (BCC) model because scale (pure) efficiency can be achieved by its application and the fact that weakness (b) does not occur with VRS model makes it a veritable basis for partitioning and the leverage for the DMUs to self-assess to estimate the restriction for the upper bound of the free variable. By this, the restriction is only placed on the free (slack) variable instead of placing the bound on the weights of input and output variables as it was previously proposed and applied. Therefore, with this modified VRS, there is no need to set any non-Archimedean infinitesimal.

Daneshvar, et al. (2014) presented three partitions for efficient DMUs according to the BCC model as (i) The strong efficient points (SEP), (ii) The efficient points (EP) and (iii) The weak efficient points (WEP). SEP are points that are located at the vertices of the frontier, EP are points that are not on the vertices of the frontier but are efficient point s at both the input and output orientations of the BCC structure. WEP are points that are neither efficient at input orientation nor efficient at output orientation. However, their method did not include the partitioning of the efficient into the analysis. This study will incorporate partitioning into the analysis of the efficient DMU. Hibiki and Sueyoshi (1999) presented a model called SA-BCC which can determine efficient DMUo at SEP, EP and WEP. Relating to the PPS, a super-efficiency BCC model was proposed by Jahanshahloo et al. (2005). Huang and Rousseau (1997) proposed a model that can estimate all the supporting hyperplanes of an efficient BCC model.

In their opinions, Zollanvari et al. (2009); Fathi et al. (2011), ANN is a veritable tool for handling complicated system's decision variables especially those with nonlinearities and interactions. ANN equally has the ability to learn from experimental data in order to predict the response values of those that were not covered during the experiment. There are many ANN architectures that are available, amongst such a well-known supervised ANNs architecture is a three (input, hidden and output) layer feed forward back propagation (BP) is adopted for the application of the model of this study. The work of Salmasnia et al. (2012b), though it does not incorporate DEA the manner of application of GA and their attempt to select adequate BPNN topology for training the model prior to prediction in the robust design was quite interesting. However, the selection was based only on the value of the mean square error (MSE) of testing and training, while the prediction was done from the normalized signal to noise ratio of the experimented data.

This present study anticipates a holistic selection of the topology through MSE and the coefficient of determination or regression coefficient R2 of training and cross-validation, and prediction will be done with the real experimental data. Selection of the adequate topology is based on the determination of the appropriate number of neurons at the hidden layer. This determination has been thoroughly carried out using different methods which according to Stathalkis (2009), includes trial and error, heuristic search, exhaustive search, pruning and constructive algorithm, and the newest genetic algorithm (GA) search. The latter would have been the most appropriate but it usually overshadows and compromises the effectiveness of the neural network.

Balestrassi et al. (2009) reported extensively applying DoE to estimate the parameters of an ANN through simulation. Taguchi, fractional and full factorial designs were employed for screening and to explored the ability to set the parameters of a feedforward multilayer perceptron neural network. Therefore this study will use a trial and error method for the evaluation and determination of the number of neuron at the hidden layer. BPNN is included in the model for prediction purposes when there are missing or censored data, as a result, uncontrollable circumstances such as impaired or faulty equipment, time inadequacy or constraint, cost limitation, human errors and such that may occur during the experiment. This situation may lead to the completion of just some parts of the experiment. Another reason could be that the experimenter may want to obtain response values beyond the inputs used during the experiment. These situations could result in data with less or incomplete information which are usually difficult to be analyzed. In these circumstances, BPNN is proposed to be used to handle the situation and its choice is predicated on its non-parametric feature and its generalization ability.

The problems with the previous DEA-BPNN applications are mostly in the use of standard DEA models (CCR and BCC) and their inability to select adequate ANN topology in their procedures. Most of these methods could not select the optimum process parameter level setting. This study seek to enhance the robustness of the application of DEA and ANN in the robust parameter design by increasing the discrimination among DMUs through the application of the modified VRS to remove the menace of VRS model by restricting the upper bound of the free variable, incorporate BPNN topology with adequate numbers of neurons at the hidden layer into the modified VRS model to predict the response for any experiment with censored, missing and incomplete experimental data or whenever data beyond those experimentally obtained are required (See Liao [2004] for example of a censored, missing or experiment with incomplete data).

The selection of the adequate process parameter level setting using the VRS penalization coefficient was also conducted. Another uniqueness of this study is in the proposition of the use of the fractional factorial number of the orthogonal array obtained for the robust parameter procedure as the number of neurons in the hidden layer of the BPNN. In the proposed model, assumptions are drastically reduced, the inputs and outputs were allowed to self-assess to produce their weights, computations are simplified, and the procedure is completely non-parametric ensuring its accuracy and its simplicity for quality engineers and managers to understand and implement.

2.3 Exergetic analysis of multicomponent distillation system

In laying a foundation for the integration of the proposed model of this study with thermoexergetic analysis, there is the need to also review some methods that have been applied to optimize and select optimum operating condition for multicomponent distillation systems involving multiresponse. Conventionally, thermo-exergetic analysis has been used successfully to examine the thermodynamic efficiency of multicomponent distillation columns as reported by Zemp et al., (1997); Mia and

Zemp, (2000), Demirel, (2013) and Alhaji and Demirel (2015). It is not an overstatement that distillation has been a widely used technique for separating about 95% of all fluids in the chemical industry and that about 3% of the total energy consumption of the world are used in distillation units (Engelien et al., 2003). Many structural alternatives have been analyzed in the studies of Alatiqi and Luyben, (1985), Finn, (1993), Fidkowski and Krolikowski, (1990), Glinos and Malone, (1998), Rong et al., (2000), Rivero and Koeijer (2003), Hsuana and Wie (2005), Flores et al, (2003), Bandyopadhyay (2002), Shin et al., (2015), and Sun et al., (2012) to determine the operation of an energy-efficient multicomponent distillation unit. Exergy analysis and optimisation are the major qualitative and quantitative tools that are used in the decision making. Various thermodynamically concepts have also been applied to optimize and select thermo-feasible multicomponent distillation systems and Dhole and Linnhof, (1993); Moussa, (2001); Faria and Zemp, (2005) concluded that if the values for the exergy losses in the rectifying and stripping section are close, then the total exergy consumption of the column is minimized and thus are deemed to be thermo-feasible. Faria (2003) showed that for some cases of separation of non-ideal mixtures, useful exergy destruction curves are not easily obtained. Demirel, (2006a, 2006b) showed that there is a very close relationship between exergy loss and driving forces, given by the distance between the operating and equilibrium line and sections with large changes in composition and temperature also show large exergy losses, while sections with small driving forces show small exergy losses. Santanu (2002) introduced diagrammatical methods that could aid in the design and retrofit of energy efficient distillation processes. Column sections or individual stages that operate under large thermodynamic inefficiency are quickly identified. Ruchira and Masaru (1996), Taparap and Ishida (1996), Kusumaningtyas et al., (2014) and Khoa, (2010) presented improved graphical methods that provided insight into column profiles.

Narvaes-Garcia et al., (2015) proposed the use of three qualities or performance indices-Luyben's capacity factor, total annual costs and annual profit to optimize a batch distillation column working at variable reflux and concluded that annual profit was the best quality index and minimum reflux was the best indicator for the optimum design of the batch distillation examined. They also submitted that for continuous distillation, energy consumption and efficiency remain the area of opportunity for distillation optimization. Ki-Joe and Diwekar (2000), Low and Sorensen (2003), Santos et al., (2012) used three performance indices-distillation parameters, energy consumption and money to discriminate between alternative for optimization. The method of equilibrium stage model and efficiency applied by Bhatt and Patel (2012), Lone and Ahmed (2012), Steffen and Da-Silva (2011) and Sing et al., (2015) was limited by the introduction of some uncertainties and variations caused largely by the effects of the uncontrollable (noise) factors that were not factored into the model used. Feyzi and Beheshti (2017) applied response surface methodology (RSM) and showed that a reduction in the exergy loss and energy consumption through predicted operating parameters. However, Cassettari et al., (2013) pointed out that one of the major assumptions of the RSM is that the experimental error that is strictly connected to the system under evaluation is fixed and cannot be controlled by the engineers. Adesina and Popooola (2016) reported that through exergy rate profile, exergy efficiency and irreversibility, the thermo-feasible system which form the basis for system improvement can be identified. They also concluded that optimization and selection of the condition for the optimum sequence for the thermo-feasible system obtained will require further thermodynamic concepts in terms of assumptions and computational search. Obviously, those uncontrollable parameters are also influencing the thermodynamics of the process.

It is so obvious that no such thermo-exegetic analysis could on its own optimize the process to obtain the optimum conditions for the adequate multicomponent distillation sequence. Little efforts have been dissipated on how to smoothen the effects of these variations. Our study basically suggests an integrated approach that seeks to consider the relationship between the controllable and the uncontrollable factors through the robust signal-to-noise ratio procedures so the thermo-exergetic responses of the system can be rendered insensitive to the effects of variations due to the noise indicators. We attempt revamping the modified Variable Return to Scale (VRS) model with the view of enhancing the discriminatory tendency of the model with the view of providing an adequate, simplistic and robust alternative to the optimum selection of the operating parameters for multicomponent distillation. As far as known, little or no studies have been conducted to integrate thermoexergetic analysis with data envelopment in the robust SN procedures for optimizing multicomponent distillation.

2.4 Previous proposed models for solving supplier selection problems in the supply chain management (SCM)

Globalization has been leading to emerging and evolving business strategies and these consequently stirred up competitions, reduction in business transaction speed or rate, revamping communication and technological ideas for the decision-making dilemma especially in supplier selection. This issue is becoming more pronounced, complicated and complex simultaneously. The convolution has been identified to be magnified through the selection problem which often requires qualifying and quantifying performance indicators. In an ultimate attempt for making the profit, it is now a matter of compulsion that supplier selection must meet customers' requirements. Therefore organizations have to be logical in their actions and strategies when appraising suppliers and therefore a good working relationship with distributors, wholesalers, retailers, customers and suppliers of various kinds in the supply chain is sacrosanct in selecting adequate supplier toward gaining competitive advantages in the markets. Competitiveness has imposed on the survival of business, quick and fast decision making in selecting the right suppliers. It is no doubt that due to product life cycles which are usually limited, and to meet up demands, concerted efforts should be geared toward manipulating varying technologies, higher standards and surge in the other supporting services in the selection process. Invariably, priority should be on using adequate procedures in appraising countless suppliers with multi-performance indicators. Supplier selection procedures as opined by Beil (2010) usually gulp huge financial resources of an organization while substantive advantages are usually expected in return from the contracting suppliers. A thorough but simplistic and well-composed procedure is needed for the decision maker to effortlessly and accurately appraise and detail the right supplier among vast potential suppliers with countless performance and parameter indicators.

Many studies such as De Boer et al. (2001), Ho et al. (2010), Wadhwa and Ravindran (2007) have been carried out and they have described various supplier evaluation criteria or indicators with the implementation of some selection models and frameworks for solving supplier selection issues within the supply chain management domain. Habib (2014) confirmed that over the previous decade diverse of multi-performance intentions had been applied toward solving supplier selection menace involving multi-performance indicator in profit-making supply chain management firms. According to Ma et al. (2014) selection parameters vary with varying conditions and because of this, there is no a clear-cut or best procedure to assess and select suppliers. Therefore different organizations tend to adopt different avenues in their appraising procedures. As reported by Mukherjee (2014) such procedures have been broadly categorized into single and integrated models. The single model uses concepts of mathematics, statistics and artificial intelligence while integrated model involved blending or incorporating two or more approaches for solving the problem. Table 1 show how those approaches that have been applied to their corresponding outputs. Amongst all proposed models, analytic hierarchy process (AHP), analytic network process (ANP) and their respective integrated models have been mostly and widely reported elsewhere like Hou and Su (2007).

Classical models especially fuzzy integrated models have been used over time for trading off between these supplier selections of different quantities (Chen et al., 2006). Nazim et al. (2015) and Nazim and Yaacob (2017) proposed integrated AHP-SCOR (Analytical Hierarchy Process-Supply Chain Operation Reference) model to improve the robustness of supplier selection system. It concluded that multi-parameters that are mostly used by researchers for solving supplier selection problem in the supply chain are cost, quality, delivery and service. Elgarra at el. (2010) had described SCOR model as a business process redesigning, standardizing, and process dimensioning as analyses that could best be practice within the supply chain as a homogeneous model. The model served as the basis for which organizations have leverage on to fix within supply chain management by filling the gaps in the chain efficiency.

Agakishiyev (2016) studied the application of Z-information technique for solving supplier selection problem where fuzzy and partially reliable information was construed by Z-number. The Z-number of desired ideal and negative ideal solution was determined. The use of partially reliable information is not a good omen for the model proposed. The proposition of the use of non-parametric data envelopment analysis either singly or incorporated has been widely reported thus this study is basically interesting and aligned with such previously used DEA concepts. A hybrid technique that incorporated multiple AHP, DEA and neural network (NN) was considered by Sung and Krishnan (2008) but the method only achieved a combined supplier score which was used for rating the supplier. Another integrated DEA-NN method appraising supplier under incomplete information was proposed by Celebi and Bayrakar (2008). Desheng (2009) added another hybrid technique with DEA-decision tree (DT) -NN, hybrid DEA-AHP and activity-based costing (ABC). This hybrid produced enhanced overall efficiency and reduced indirect expenses. Integrated multiple multi-criteria decision making (MCDM) of Parthiban et al. (2013) clipped fuzzy logic and strength-weakness-opportunity-threat (SWOT) into DEA (also see MCDM of Wadhwa and Ravindran (2007)). According to Zeydan et al. (2011), the combination of Fuzzy AHP, Fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and DEA could be used. This effort led to the use of a dummy input for the DEA method. A DEA cross efficiency design was conducted by Noorizadeh et al. (2012) to solve supplier selection problem by trying to treat undetected outputs in a way that it will be much easier to completely rank them and to eradicate unrealistic weighing plans amongst DMUs. So also did Mahdiloo et al. (2012). Sean (2007)'s imprecise DEA was used to evaluate supplier selection using all available data both quantitative and qualitative but failed in dimensioning the system legitimately. An augmented imprecise DEA methodology applied by Wu et al. (2007) which was an improvement on Sean's (2007) exploit was able to properly handle imprecise data and also brought about an improved discriminatory tendency of the model.

A structured methodology where SWOT was used to first to identify germane criteria and indicators, fuzzy weight scheme to determine weight of the indicators, DEA to screen potential supplier, TOPSIS and MADA (multi-attribute decision making Analysis) was used for ranking was proposed by Chen (2011) which involve the use of Delphi technique as slated in Chou (2002). A Constant Return to Scale (CRS) DEA model, where a rigid relationship between input criteria and output indicators would force them to produce equal efficiency at both orientations was used. Moreover, the weakness of the CRS model used which is the tendency of the model to produce a misleading result by promoting DMUs with inadequate weight as the efficient system was not dealt with. However, Mukherjee (2014) revealed that fuzzy is unsuitable because it can deal with the uncertainties that are associated with the variation and assigning suitable fuzzy number is completely prejudiced and circumstantial. Fuzzification of the multi-parameter indicators is also unable to guaranty optimum solution. But instead, it leads to complications of the existing algorithm which is evident by prolonging computational time. Further perceived issues with Chen (2011) were that lower discriminatory tendency of the proposed model through the method successfully established an evaluation framework for supplier integration in supply chain management. This framework was proposed in three phases. Phase 1 is the requirement and strategy analysis under which SWOT was used as a tool at competitive strategy identification for appraising and identifying criteria and indicators for supplier selection. A three-step phase 2 supplier evaluation consist of candidate supplier selection step where DEA was introduced, the weight of decision indicators under evaluation step estimated weight using fuzzy weight technique and supplier evaluation step where TOPSIS was used as the tool. Delphi questionnaire technique was used at phase 3 for assessing suppliers' performance.

Chapter 3

MODELS AND METHODS CONSIDERED IN THE PROPOSED MODIFIED VRS-ROBUST PARAMETER PROCEDURE

3.1 Phases and Models considered

In this study a robust intelligent procedure was developed for solving multiple response problems in the Taguchi the robust parameter signal-to-noise ratio strategy, artificial neural network and modified data envelopment analysis model. This modification termed facet analysis resolved the shortcomings of the previous applications.

3.2 Robust parameter design

Robustness is achieved by posing Signal-to-Noise ratios (SN) as a measure of performance such that each process or product will have an anticipated target or simply a nominal value. This made SN a veritable tool for evaluating the quality of a process or product by measuring the degree of quality performance against the level of noise factors. Simply put according to Belavendram 1995, SN which can either be positive or negative value, is an evaluation of the stability of the efficiency or performance of an output attribute. As expression as given by Taguchi et al. (2005), SN has been defined for various problems as follows;

Larger-The-Better (LTB),

$$\mathrm{SN} = -10\log\left(\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{n}\frac{1}{\mathrm{y}_{ij}^{2}}\right),\ \text{for } j = 1, 2, \dots, k \tag{1}$$

Smaller-The-Better (STB)

$$\mathrm{SN} = -10\log\left(\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{n}\mathrm{y}_{ij}^{2}\right), \text{for } j = 1, 2, \dots, k \tag{2}$$

Nominal-The-Better (NTB);

$$\mathrm{SN} = \quad 10\log\left(\frac{\overline{\mathrm{y}}_{ij}^{2}}{\mathrm{s}_{ij}^{2}}\right), \text{for } i = 1, 2, \dots, \mathrm{n};\ \text{for } j = 1, 2, \dots, k$$

(3) Similarly, Normalized Signal-to-Noise-ratio (NSN) is estimated respectively for LTB, STB and NTB according to the method of Zulfigar, (2014);

$$\mathrm{NSN_{ij}} = \frac{\mathrm{Y}_{ij} - \min(\mathrm{Y}_{i\,j}\ i{=}i{=}1,2,\dots,n)}{\max(\mathrm{Y}_{i\,j}\ i{=}i{=}1,2,\dots,n) - \min(\mathrm{Y}_{i\,j}\ i{=}1,2,\dots,n)} \tag{4}$$

$$\mathrm{NSN_{ij}} = \frac{\min(\mathrm{Y}_{i\,j,}\ i{=}1,2,\dots,n) - \mathrm{Y}_{ij}}{\max(\mathrm{Y}_{i\,j,}\ i{=}1,2,\dots,n - \min(\mathrm{Y}_{i\,j,}\ i{=}1,2,\dots,n)} \tag{5}$$

$$\mathrm{NSN_{ij}} = \frac{|\mathrm{Y}_{ij} - \mathrm{Target}| - \min(|\mathrm{Y}_{i\,j} - \mathrm{Target}|,\ \ i{=}1,2,\dots,n)}{\max(|\mathrm{Y}_{i\,j} - \mathrm{Target}|,\ \ i{=}1,2,\dots,n) - \min(|\mathrm{Y}_{i\,j} - \mathrm{Target}|,\ \ i{=}1,2,\dots,n)} \tag{6}$$

for all $j = 1, 2, \dots, k$.

Where

n is number of observation, y_{ij} is observed data, *i* is the input into the robust parameter which is the output anticipated for the experiment, *j* is the DMU, s_{ij}^{2} is the variance, $\overline{\mathrm{y}}_{ij}^{2}$ is the standard deviation and *k* is the number of DMU.

3.3 Artificial Neural Network selections

However, the selection was based only on the value of the mean square error (MSE) of testing and training, while the prediction was done from the normalized signal to noise ratio of the experimented data, this present study anticipates a holistic selection of the topology through MSE and the coefficient of determination or regression coefficient R^2 of training and cross-validation, and prediction be done with the real experimental data. Selection of the adequate topology is based on the determination of the appropriate number of neurons at the hidden layer. This determination has been thoroughly carried out using different methods which according to Stathalkis (2009), includes trial and error, heuristic search, exhaustive search, pruning and constructive algorithm, and the newest genetic algorithm (GA) search. The latter would have been the most appropriate but it usually overshadows and compromises the effectiveness of the neural network. Therefore this study adopted use trial and error method for the evaluation and determination of the number of neuron at the hidden layer.

The topology of the BP neural network with a hidden layer-based process model was adopted for this study. For the networks, the middle layer uses the activation function of tangent hyperbolic and output layers using a sigmoid function. Training algorithm in networks was Levenberg- Marquardt supervised learning. The topology with the lowest mean squared error (MSE) and root mean square error (RMSE) closest to 1 is selected as the adequate BPNN topology.

3.4 Modified VRS model

3.4.1 VRS Partitioning of Decision Making Units (DMUs)

Daneshvar *et al.,* (2014) gave insight into how partitioning of the VRS model can result in three distinctive points namely; efficient (EP) or strong efficient point (SEP) when $\theta = 1$ and $\eta = 1$ (or vice versa), weak efficient point (WEP) when $\theta = 1$ and $\eta < 1$ (or vice versa) and inefficient point when $\theta < 1$ and $\eta < 1$. It was proofed that for the optimal solution of standard VRS model, the global optimal solution u_o^* should satisfy the inequality that $u_o^{-*} \leq u_o^* \leq u_o^{+*}$. For instance at input orientation, if $u_o^{+*} = 1$ such that the inequality becomes $u_o^{-*} \leq u_o^* \leq 1$, and then there exists an intersection between WEP and EP. This connotes that if it is possible that the free variable u_o^* can be restricted in such a way that, the free variable can be strictly less than 1, then it is possible to completely disperse or partition the frontier into EPs and WEPs. This position was also inferred by Daneshvar (2009). Therefore finding a restriction for the upper bound denoted as ε for the free variable of the standard VRS model can be adequate for removing the weakness of the classical/standard VRS model. The study imposed partitioning within the model and the model self-evaluated to estimate its own input and output weights. Graphically, partitioning can be explained as represented in the figure in Appendix A.

To solve the weakness (b) identified in the section1, Data Envelopment Analysis is carried out to determine the efficiency scores at both input and output orientations. For standard VRS (BCC) at input-orientation, the efficiency score (θ) as applied by Daneshvar, *et al.*, (2014) is expressed as;

$$\theta = Max \sum_{r=1}^{s} u_r y_{ro} + u_o$$

$$\begin{aligned} S.t.\ & \textstyle\sum_{i=1}^{m} v_i x_{io} = 1 \\ & \textstyle\sum_{r=1}^{s} u_r\, y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + u_o \le 0 \\ & u_r \ge 0 \quad r = 1, \dots s \\ & v_i \ge 0 \quad i = 1, \dots m \\ & u_o \ free \end{aligned} \tag{7}$$

Similarly, at output-orientation efficiency score (η) is obtained by

$$\eta = Min \ \textstyle\sum_{i=1}^{m} v_i x_{io} + v_o$$

$$\begin{aligned} S.t.\ & \sum_{r=1}^{s} u_r y_{ro} = 1 \\ & \textstyle\sum_{r=1}^{s} u_r\, y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + v_o \le 0 \\ & u_r \ge 0 \quad r = 1, \dots s \\ & v_i \ge 0 \quad i = 1, \dots m \\ & u_o \ free \end{aligned} \tag{8}$$

Where;

y_{ro} is the output of the DMU under investigation, x_{ij} is the input data DMU*j*, y_{rj} *is the* output data to DMU*j*, v_i is the input weight, u_r is the output weigh, u_o is the upper bound of free variable of the optimal solution, *m* is the total number of input data, *s* is the number of output data, *r* is the output, *k* (*j* = 1, …, *k*) the number of the DMU, u_o^* is the global optimal value of the free variable, u_o^{+*} is the free variable optimal value at the output maximization, u_o^{-*} is the free variable optimal value at the output minimization, subscript *o* denotes the DMU under investigation.

3.4.2 Modified (Facet) VRS model

In the modified VRS super efficiency model of Daneshvar *et al.*, (2014), the free variables of the standard VRS model is restricted to an upper bound denoted as ε;

$$\varepsilon = \max\{u_o^- / u_0^+ \neq 1 \quad for\ efficient\ DMUs\} \tag{9}$$

Then u_o^-, is obtained solving;

$$\begin{aligned} &Min \quad u_o \\ &\text{S.t.} \quad \boldsymbol{u^t} y_o + u_o = 1 \\ &\boldsymbol{v^t} x_o = 1 \\ &\boldsymbol{u^t} \geq 0 \\ &\boldsymbol{v^t} \geq 0 \\ &u_o \ free \end{aligned} \tag{10}$$

Then u_o^+, is obtained solving;

$$\begin{aligned} &Max \quad u_o \\ &\text{S.t.} \quad \boldsymbol{u^t} y_o + u_o = 1 \\ &\boldsymbol{v^t} x_o = 1 \\ &\boldsymbol{u^t} y_o - v^t x_o \leq 0 \\ &\boldsymbol{u^t} \geq 0 \\ &\boldsymbol{v^t} \geq 0 \\ &u_o \ free \end{aligned} \tag{11}$$

The modified VRS model is now written as;

$$\begin{aligned} &Max \quad \boldsymbol{u^t} y_o + u_o \\ &\textbf{S.t.} \quad \boldsymbol{v^t} x_o = 1 \\ &\boldsymbol{u^t} y_o - u^t x_o, i = 1 \\ &\boldsymbol{u^t} \geq 0 \qquad r = 1, \dots s \\ &\boldsymbol{v^t} \geq 0 \qquad i = 1, \dots m \\ &u_o \leq \varepsilon \end{aligned} \tag{12}$$

Where, u^t is the output weight vector, v^t is the input weight vector determined through the self-evaluation of the DMUs and u_o is the optimal value of the free variable for the modified VRS model.

Seiford and Zhu (1999) reported that the super-efficiency DEA method has some shortcomings Therefore aside from imposing partitioning, we equally propose that the revamped facet VRS model should self-evaluate (DMU appraises itself) to estimate their input and output weights thereby no assumption is made in this regard. Equation 12 estimates the pure technical efficiency of the industry technology level that the production process of a production unit reaches. For this, our study employs the output orientation thereby under the condition of the given input of the distillation operating parameters; the objective (Equation 12) is the degree of maximization of the objective function.

3.5 VRS Penalization

For optimum DMU selection from the efficient points obtained by the modified VRS model, second VRS DEA model for the estimation of the penalization coefficient W_J of the weight of the response as given by Gutierrez and Lozano (2010) where W_J the penalization coefficient of DMUJ is, J is the index of factor combination to be evaluated. The index of factor as used here connotes the particular DMU whose penalty is to be derived. Here, only to the input (NSNs) of the particular efficient DMU index J is involved. Hence;

$$\begin{aligned} & \text{Max } \mathrm{W}_J \\ \text{S.t.} \quad & \textstyle\sum_{i=1}^{q} \mathrm{u}_i \mathrm{NSD}_{ij} \geq 1 \quad \nabla j \neq J \\ & \textstyle\sum_{i=1}^{q} \mathrm{u}_i \mathrm{NSD}_{iJ} = 1 \\ & \mathrm{u}_i \geq \mathrm{W}_J \\ & \mathrm{W}_J \geq 0 \end{aligned} \tag{13}$$

Where q is the number of efficient DMU obtained by the modified VRS model such that index J = 1, 2,…,q and for $i = 1, 2, \dots, n$.

Chapter 4

PROPOSED REVAMPED FACET ANALYZED VRS IN THE ROBUST PARAMETER DESIGN PROCEDURES

4.1 Model Conception

This modified VRS- robust parameter model was achieved in four phases: data collection and generation, responses evaluation using experimental data or artificial neural network as the case may be, robust parameter procedures, DEA partitioning using standard VRS models, evaluation of DMU that compare with WEPs using modified VRS, and optimization to determine and select optimum factor level combination by VRS penalization coefficient.

4.2 Model Development

The proposed framework as presented in Figure 3 illustrates the phases involve in the proposed model as thus;

4.2.1 Phase A (Data generation and collection)

The major aim of this phase is to gather data for signal-to-noise ratio estimation using the input and output data from obtained experimental data or neural network prediction for factor level combination and response prediction as the case may be. This phase consists of three steps:

Step 1 (identifying controllable factors). In this phase, process operating parameters are determined.

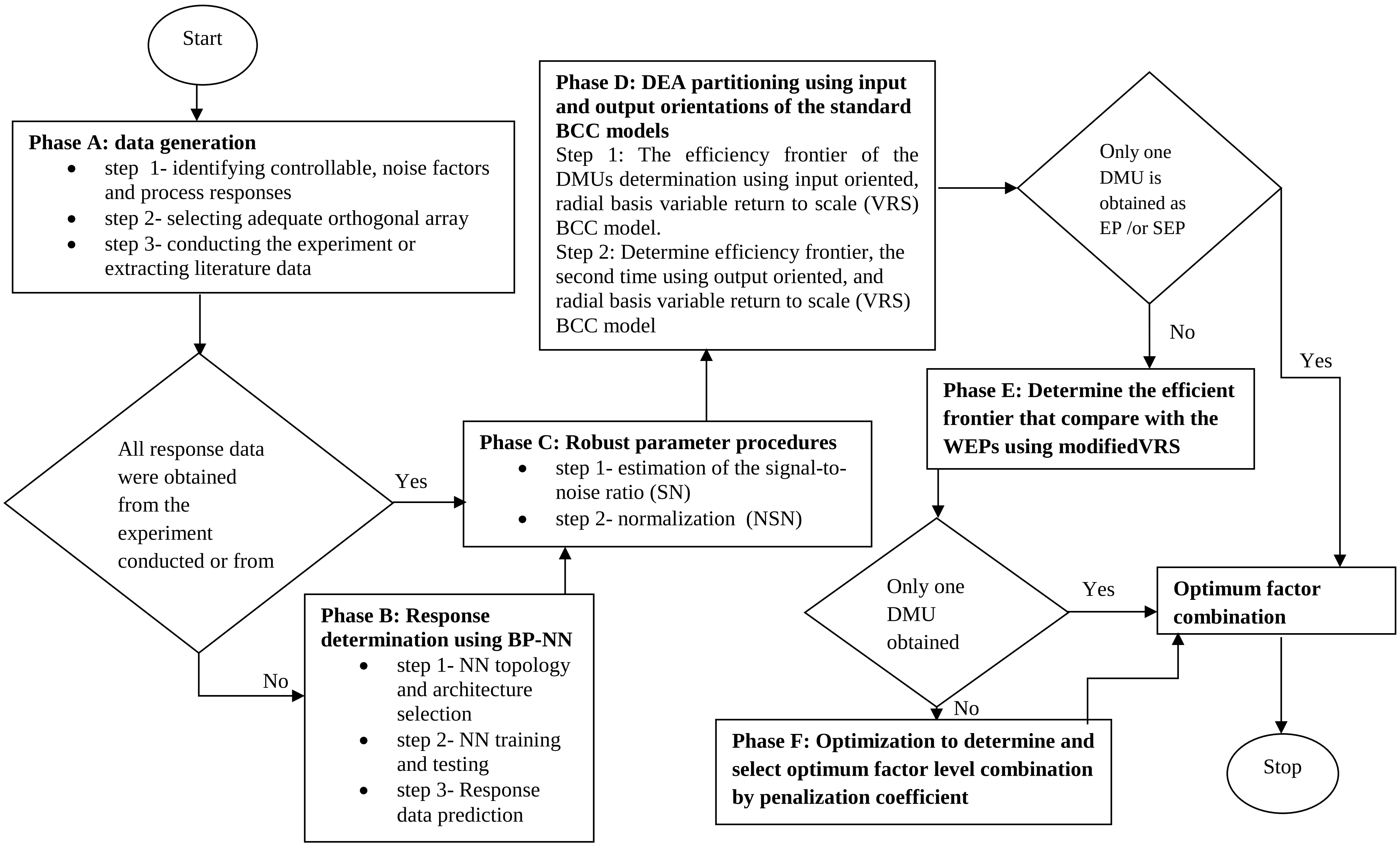


Figure 3. Proposed modified VRS-BPNN framework for solving multiple response experiment in the robust parameter procedures

Step 2 (selecting adequate orthogonal array). An orthogonal array was selected according to the levels of control and noise factors.

Step 3 (Conducting the experiment).

4.2.2 Phase B (response evaluation using artificial neural network)

The topology should consist of an input layer with two neurons, one hidden layer and output layer with three neurons. Trial and error search is conducted to determine the number of neurons that should be in the hidden layer. Neural fitting (nftool) that uses feed-forward back propagation training algorithm of Levenberg-Marquart, is selected from the Neural Network toolbox 8.2 of Matlab 2014a. The hidden layer is transformed by the sigmoid function while the output layer uses a linear fit function for its transformation of data. Adequate topology is selected based on MSE and the coefficient of determination or regression coefficient R2 values of both training and cross-validation outputs. BPNN is included in the model for prediction purposes when there are missing or censored data as a result of uncontrollable circumstances such as impaired or faulty equipment, time inadequacy or constraint, cost limitation, human errors and such that may occur during the experiment. This situation may lead to the completion of just some parts of the experiment. Another reason could be that the experimenter may want to obtain response values beyond the inputs used during the experiment. These situations could result in data with less or incomplete information which are usually difficult to analyze. In these circumstances, BPNN is proposed to be used to handle the situation and its choice is predicated on its non-parametric feature and its generalization ability.

By this BPNN step, the proposed model could be viable and applicable for all situations as its redundancy especially when censored or missing data are encountered can be avoided. This study presents means of training and validating to select the adequate BPNN topology that can be used to determine the missing data when encountered. This steps involves are;

Step 1 (neural network topology and architecture selection). MATLAB 2016a is used for the neural network and neural fitting tool (nftool) was selected since the network will be used for prediction.

Step 2 (training, testing and validating the BP-ANN). An adequate BPNN topology and architecture was trained, tested and validated using the actual experimental data. The values of the factor levels combinations are set as input at the input layer with their corresponding normalized signal-to-noise ratio of each response set as the target in the output layer. Step 3 (factor levels and corresponding signal-to-noise ratio prediction). A well trained, tested and validated BPNN topology and architecture was used to predict the SN ratios for all possible control factor levels combinations.

4.2.3 Phase C (Robust Parameter Procedures)

This comprises three steps as

*Step 1: S*electing adequate orthogonal array. An orthogonal array was selected according to the levels of control and noise factors.

*Step 2: E*stimation of signal-to-noise ratios (SN) of responses from experimental data obtained.

Step 3: Normalized signal-to-noise-ratio estimation NSNs.

4.2.4 Phase D VRS Partitioning (Determination of the efficiency point, weak efficiency point and strong efficiency point (DEA partitioning) using input and output orientations of the standard BCC models)

Step 1: estimation of the weights of the efficient frontier via *input oriented,* radial basis variable return to scale BCC model.

Step 2: estimation of the weights of the efficient frontier via using *output oriented* radial basis variable return to scale model.

Step 3: Evaluation of the EP and SEP DMUs.

For steps 1-3, MaxDEA 6. 0 was used to for solving the standard VRS DEA models. The multiplier model of the software was selected instead of the envelopment model as the appropriate model for the VRS since one or more of the output values will be zero due to normalization and the output orientation of envelopment model cannot process zero value.

4.2.5 Phase E Modified VRS efficiency determination (Determine the efficient frontier that compare with the WEPs using modified DEA)

Determine the efficient frontier that using the modified VRS model. *Step 4:* Determination of the efficient frontier that compare with the WEPs DMUs by modified VRS conditions using weights estimated in steps 1-2 in Section 4.2.4 above and the upper bound of the free variables ε.

4.2.6 Phase F (Optimization to determine and select optimum factor level combination by penalization coefficient)

This phase becomes necessary when efficient frontier EP and efficient DMU obtained from modified method comes out to be more than one DMU. To optimize and select optimum DMU, VRS penalization coefficient is carried out on the efficient DMUs obtained in Phase 5. This is aimed at allowing each efficient factor level combination to assign different weight to the NSN of their responses. At this juncture, it should be noted that the penalization coefficient step is not indicating the efficiency score of those efficient systems but rather it is a check on the efficacy of each efficient parameter setting to produce its equivalent maximum lower bound which is a kind of penalty that can be imposed on the response variables. This is possible by allowing each efficient system to once again self-evaluate to re-assess and assign different weights to the NSN of their input and output weights in order to determine an indicator- penalization coefficient. This step replaces setting of any trade-off between variables as they can through the VRS penalization interrelate within themselves to produce the optimum. For both phases E and F, linear programming models were generated and solved using LINDO 6.18 software.

Chapter 5

NUMERICAL ILLUSTRATION OF THE PROPOSED MODEL

5.1 Optimizing hard disk drive case study

Procedure A (steps 1-3): As reported by Phadke 1989, the quality of hard disk drive was investigated with four responses; 50% pulse width (PW), peak shift (PS), overwrite (OW), and high-frequency amplitude (HFA). The PW and PS are STB type responses, OW and HFA are LTB type responses. Five controllable process factors used for the investigation involve (A) disk writability, (B) magnetization width, (C) gap length, (D) coercivity of media, and (E) rotational speed. The input and response data of hard disc as given by Al-Refaie and Al-Tahat (2011) is presented in Table 1. A total of 18 parameter level combinations were achieved, therefore L_{18} orthogonal array was adopted for the robust parameter procedure and hence we have 18 DMUs for this case study.

Procedure B (steps 1-3): From Fig. 3, this step is not required here since all the data have been obtained from the experiment and no further data beyond those obtained by the experiment is needed.

Table 1. Input and output data for the hard disc case study

DMUs	**Process parameter setting (Input Variables)**					**Responses (Output Variables)**			
	A	B	C	D	E	PW50	PS	OW	HFA
1	1	1	1	1	1	64.75	11.45	31.15	272.15
2	1	1	2	2	2	65.10	12.30	34.05	326.80
3	1	1	3	3	3	66.30	14.15	35.75	367.75
4	1	2	1	1	2	55.55	10.00	32.50	311.75
5	1	2	2	2	3	57.00	10.70	35.55	350.65
6	1	2	3	3	1	88.40	18.45	39.20	223.90
7	1	3	1	2	1	64.85	10.95	30.60	273.60
8	1	3	2	3	2	65.20	11.40	34.55	320.35
9	1	3	3	1	3	66.25	14.90	45.10	297.75
10	2	1	1	3	3	48.60	11.40	18.95	422.40
11	2	1	2	1	1	75.95	17.10	33.10	277.30
12	2	1	3	2	2	75.70	17.75	34.45	329.60
13	2	2	1	2	3	48.60	10.80	24.05	420.85
14	2	2	2	3	1	76.00	15.55	29.30	296.65
15	2	2	3	1	2	75.70	18.60	38.65	258.65
16	2	3	1	3	2	55.55	12.50	18.80	360.95
17	2	3	2	1	3	57.00	12.75	35.10	360.10
18	2	3	3	2	1	88.35	20.35	37.75	257.60

Procedure C

Step 1: estimate the S/N of responses by applying Equation (3) to PW and PS and Equation (2) to OW (treated as STB according to Al-Refaie (2012) and HFA. For illustration, for DMU 1;

$$\frac{\mathrm{S}}{\mathrm{N}}, \mathrm{PW} = -10 * \mathrm{LOG}(64.75)\hat{}2 = -36.22479$$

$$\frac{\mathrm{S}}{\mathrm{N}}, \mathrm{PS} = -10 * \mathrm{LOG}(11.45)\hat{}2 = -21.176109$$

$$\frac{\mathrm{S}}{\mathrm{N}}, \mathrm{OW} = -10 * \mathrm{LOG}(31.15)\hat{}2 = 29.86916$$

$$\frac{\mathrm{S}}{\mathrm{N}}, \mathrm{HFA} = -10 * \mathrm{LOG}(\frac{1}{272.15})\hat{}2 = 48.6961$$

Step 2: estimate the NSN of the S/Ns by applying Equations (4 and 5) appropriately.

To illustrate illustrated for DMU 1: as:

$$\mathrm{NSN, PW} = \frac{-33.73272 - (-36.22479)}{-33.73272 - (-38.92413)} = 0.4800$$

$$\mathrm{NSN, PS} = \frac{20.00 - (-21.176109)}{-20.00 - (-26.17128)} = 0.1906$$

$$\mathrm{NSN, OW} = \frac{29.86916 - 25.48315}{33.08353 - 25.48315} = 0.5771$$

$$\mathrm{NSN, HFA} = \frac{48.6961 - 47.00108}{52.51447 - 47.00108} = 0.3074$$

The same calculations are repeated for the remaining DMUs.

Procedure D

Step 1: Solve the standard VRS model in Equation 7 using MaxDEA 6.0 version software.

Step 2: Solve the standard VRS model in Equation 8 using MaxDEA 6.0 version software.

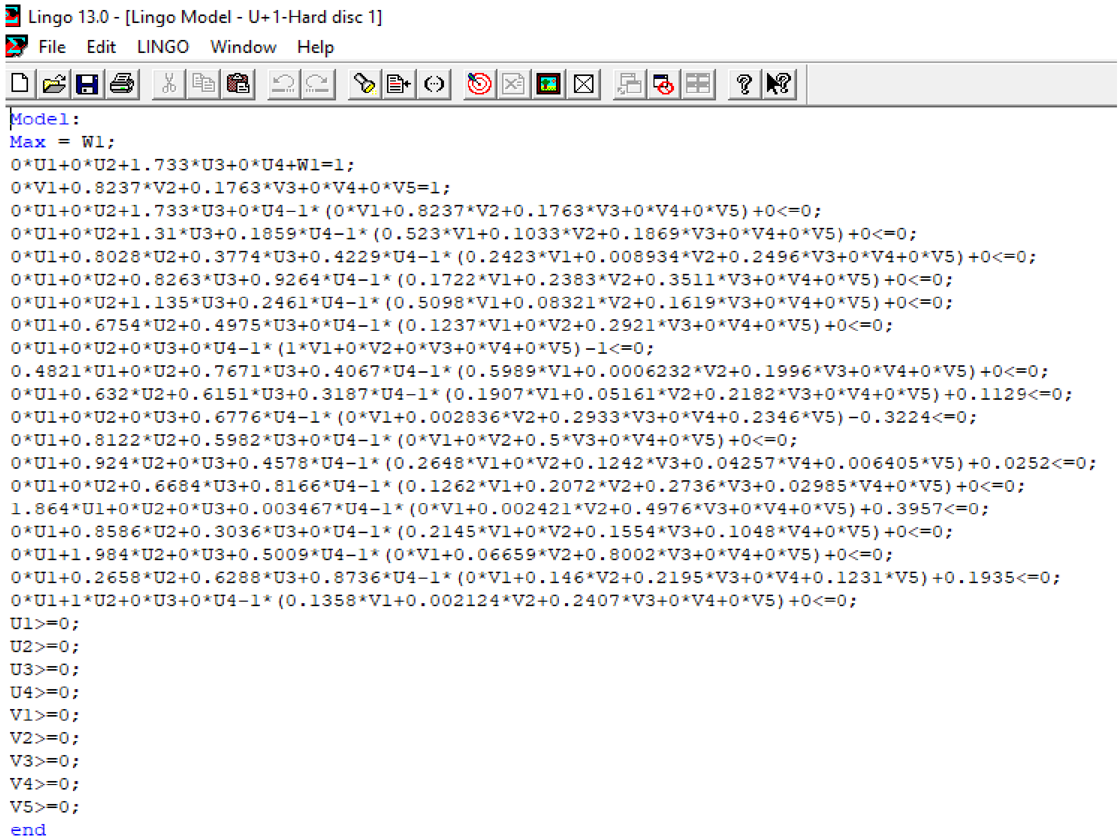
The input and output weights obtained are shown in Table 2.

Step 3: Extract the efficiency scores obtained from step 1, ($\boldsymbol{\theta}$) and 2 ($\boldsymbol{\eta}$). If a DMU is efficient at both orientations, then it is EP/SP otherwise it is a WEP.

Step 4: From the data in Table 2, solve Equation 10 and 11 to obtain u_o^+ and u_o^- respectively; for DMU 1, using LINGO 6.18 (Figure 4).

Table 2. Input and output weight obtained from the input orientation of the standard VRS models for hard disk

Weight (A)	Weight (B)	Weight (C)	Weight (D)	Weight (E)	Weight (PW50)	Weight (PS)	Weight (OW)	Weight (HFA)	u_o
0.0000	0.8237	0.1763	0.0000	0.0000	0.0000	0.0000	1.7330	0.0000	0.0000
0.5230	0.1033	0.1869	0.0000	0.0000	0.0000	0.0000	1.3100	0.1859	0.0000
0.2423	0.0089	0.2496	0.0000	0.0000	0.0000	0.8028	0.3774	0.4229	0.0000
0.1722	0.2383	0.3511	0.0000	0.0000	0.0000	0.0000	0.8263	0.9264	0.0000
0.5098	0.0832	0.1619	0.0000	0.0000	0.0000	0.0000	1.1350	0.2461	0.0000
0.1237	0.0000	0.2921	0.0000	0.0000	0.0000	0.6754	0.4975	0.0000	0.0000
1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-1.0000
0.5989	0.0006	0.1996	0.0000	0.0000	0.4821	0.0000	0.7671	0.4067	0.0000
0.1907	0.0516	0.2182	0.0000	0.0000	0.0000	0.6320	0.6151	0.3187	0.1129
0.0000	0.0420	0.0736	0.0000	0.2948	0.0000	0.0000	0.0000	0.8513	-0.1487
0.0000	0.0000	0.5000	0.0000	0.0000	0.0000	0.8122	0.5982	0.0000	0.0000
0.2659	0.0043	0.1255	0.0437	0.0000	0.0000	0.9351	0.0000	0.4413	0.0240
0.1262	0.2072	0.2736	0.0299	0.0000	0.0000	0.0000	0.6684	0.8166	0.0000
0.0000	0.0024	0.4976	0.0000	0.0000	1.8640	0.0000	0.0000	0.0035	0.3957
0.2145	0.0000	0.1554	0.1048	0.0000	0.0000	0.8586	0.3036	0.0000	0.0000
0.0000	0.0666	0.8002	0.0000	0.0000	0.0000	1.9840	0.0000	0.5009	0.0000
0.0000	0.0922	0.3617	0.0000	0.0000	0.0000	0.5099	1.2080	0.7628	0.6077
0.1358	0.0021	0.2407	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000




```
Model:
Max = W1;
0*U1+0*U2+1.733*U3+0*U4+W1=1;
0*V1+0.8237*V2+0.1763*V3+0*V4+0*V5=1;
0*U1+0*U2+1.733*U3+0*U4-1*(0*V1+0.8237*V2+0.1763*V3+0*V4+0*V5)+0<=0;
0*U1+0*U2+1.31*U3+0.1859*U4-1*(0.523*V1+0.1033*V2+0.1869*V3+0*V4+0*V5)+0<=0;
0*U1+0.8028*U2+0.3774*U3+0.4229*U4-1*(0.2423*V1+0.008934*V2+0.2496*V3+0*V4+0*V5)+0<=0;
0*U1+0*U2+0.8263*U3+0.9264*U4-1*(0.1722*V1+0.2383*V2+0.3511*V3+0*V4+0*V5)+0<=0;
0*U1+0*U2+1.135*U3+0.2461*U4-1*(0.5098*V1+0.08321*V2+0.1619*V3+0*V4+0*V5)+0<=0;
0*U1+0.6754*U2+0.4975*U3+0*U4-1*(0.1237*V1+0*V2+0.2921*V3+0*V4+0*V5)+0<=0;
0*U1+0*U2+0*U3+0*U4-1*(1*V1+0*V2+0*V3+0*V4+0*V5)-1<=0;
0.4821*U1+0*U2+0.7671*U3+0.4067*U4-1*(0.5989*V1+0.0006232*V2+0.1996*V3+0*V4+0*V5)+0<=0;
0*U1+0.632*U2+0.6151*U3+0.3187*U4-1*(0.1907*V1+0.05161*V2+0.2182*V3+0*V4+0*V5)+0.1129<=0;
0*U1+0*U2+0*U3+0.6776*U4-1*(0*V1+0.002836*V2+0.2933*V3+0*V4+0.2346*V5)-0.3224<=0;
0*U1+0.8122*U2+0.5982*U3+0*U4-1*(0*V1+0*V2+0.5*V3+0*V4+0*V5)+0<=0;
0*U1+0.924*U2+0*U3+0.4578*U4-1*(0.2648*V1+0*V2+0.1242*V3+0.04257*V4+0.006405*V5)+0.0252<=0;
0*U1+0*U2+0.6684*U3+0.8166*U4-1*(0.1262*V1+0.2072*V2+0.2736*V3+0.02985*V4+0*V5)+0<=0;
1.864*U1+0*U2+0*U3+0.003467*U4-1*(0*V1+0.002421*V2+0.4976*V3+0*V4+0*V5)+0.3957<=0;
0*U1+0.8586*U2+0.3036*U3+0*U4-1*(0.2145*V1+0*V2+0.1554*V3+0.1048*V4+0*V5)+0<=0;
0*U1+1.984*U2+0*U3+0.5009*U4-1*(0*V1+0.06659*V2+0.8002*V3+0*V4+0*V5)+0<=0;
0*U1+0.2658*U2+0.6288*U3+0.8736*U4-1*(0*V1+0.146*V2+0.2195*V3+0*V4+0.1231*V5)+0.1935<=0;
0*U1+1*U2+0*U3+0*U4-1*(0.1358*V1+0.002124*V2+0.2407*V3+0*V4+0*V5)+0<=0;
U1>=0;
U2>=0;
U3>=0;
U4>=0;
V1>=0;
V2>=0;
V3>=0;
V4>=0;
V5>=0;
end
```

Figure 4. Lingo window showing the linear programming formulation for the upper bound variable restriction.

The remaining DMUs are calculated in the same manner and the results are presented in Table 3. Equation 9 is used to determine the upper bound restriction obtained as ε = 0.3957.

Table 3. The values of u_o^-, u_o^+ for efficient DMUs for the hard disc case study

DMUs	u_o^-	u_o^+
1	0.0000	1.0000
2	0.0000	1.0000
3	0.0000	1.0000
4	0.0000	1.0000
5	0.0000	1.0000
6	0.0000	1.0000
7	1.0000	1.0000
8	0.0000	1.0000
9	0.1129	1.0000
10	0.0000	1.0000
11	0.0000	1.0000
12	0.0252	1.0000
13	0.0000	1.0000
14	0.3957	1.0000
15	0.0000	1.0000
16	0.0000	1.0000

$$\varepsilon = \mathrm{Max}\, u_o^+/u_o^- \neq 1 = 0.3957$$

Using restriction obtained for the upper bound for the modification of VRS mode, the input value and the NSN values in Table 4, we solved Equation 12 for DMU 1 as shown in Figure 5.

Procedure E: Equation 13 is solved for penalization coefficient W_J, for only the efficient DMUs obtained in procedure D above. For DMU 1, we estimated W_J to be 0.5551 by solving the expression shown in Figure 6.

Table 4. Efficiency scores for the standard orientations, modified BCC model and penalization coefficient for the hard disc case study

						Robust Parameter												
Design factors (Input Variables)						Normalized Signal-to-Noise ratio (NSN)				Signal-to-Noise ratio (SN)				VRS Modified Model				
DMU	**A**	**B**	**C**	**D**	**E**	**PW50**	**PS**	**OW**	**HFA**	**PW50**	**PS**	**OW**	**HFA**	**Score (θ)**	**Score (η)**	**Partitioning**	**Modified**	**Penalization Coefficient**
1	1	1	1	1	1	0.4800	0.1906	0.5771	0.3074	-36.22	-21.18	29.87	48.70	1.0000	1.0000	EP,SEP	1.0000	0.5551
2	1	1	2	2	2	0.4891	0.2914	0.6788	0.5957	-36.27	-21.80	30.64	50.29	1.0000	1.0000	EP,SEP	1.0000	0.4720
3	1	1	3	3	3	0.5196	0.4886	0.7345	0.7817	-36.43	-23.02	31.07	51.31	1.0000	1.0000	EP,SEP	1.0000	0.3961
4	1	2	1	1	2	0.2236	0.0000	0.6256	0.5215	-34.89	-20.00	30.24	49.88	1.0000	1.0000	EP,SEP	1.0000	0.7296
5	1	2	2	2	3	0.2667	0.0952	0.7281	0.7067	-35.12	-20.59	31.02	50.90	1.0000	1.0000	EP,SEP	1.0000	0.5566
6	1	2	3	3	1	1.0009	0.8620	0.8398	0.0000	-38.93	-25.32	31.87	47.00	1.0000	1.0000	EP,SEP	1.0000	0.3700
7	1	3	1	2	1	0.4826	0.1277	0.5567	0.3158	-36.24	-20.79	29.71	48.74	1.0000	1.0000	EP,SEP	1.0000	0.6744
8	1	3	2	3	2	0.4916	0.1844	0.6955	0.5643	-36.28	-21.14	30.77	50.11	1.0000	1.0000	EP,SEP	0.9902	
9	1	3	3	1	3	0.5184	0.5613	1.0000	0.4491	-36.42	-23.46	33.08	49.48	1.0000	1.0000	EP,SEP	1.0000	0.3954
10	2	1	1	3	3	0.0000	0.1844	0.0091	1.0000	-33.73	-21.14	25.55	52.51	1.0000	1.0000	EP,SEP	1.0000	0.8379
11	2	1	2	1	1	0.7470	0.7551	0.6465	0.3370	-37.61	-24.66	30.40	48.86	1.0000	1.0000	EP,SEP	1.0000	0.4023
12	2	1	3	2	2	0.7415	0.8076	0.6922	0.6092	-37.58	-24.98	30.74	50.36	1.0000	1.0000	EP,SEP	1.0000	0.3508
13	2	2	1	2	3	0.0000	0.1083	0.2815	0.9942	-33.73	-20.67	27.62	52.48	1.0000	1.0000	EP,SEP	1.0000	0.7225
14	2	2	2	3	1	0.7481	0.6214	0.5071	0.4432	-37.62	-23.83	29.34	49.44	1.0000	1.0000	EP,SEP	1.0000	0.4311
15	2	2	3	1	2	0.7415	0.8734	0.8236	0.2273	-37.58	-25.39	31.74	48.25	1.0000	1.0000	EP,SEP	1.0000	0.3751
16	2	3	1	3	2	0.2236	0.3141	0.0000	0.7523	-34.89	-21.94	25.48	51.15	1.0000	1.0000	EP,SEP	1.0000	0.7752
17	2	3	2	1	3	0.2667	0.3419	0.7135	0.7486	-35.12	-22.11	30.91	51.13	1.0000	1.0000	EP,SEP	1.0000	0.4829
18	2	3	3	2	1	1.0000	1.0000	0.7967	0.2209	-38.92	-26.17	31.54	48.22	1.0000	1.0000	EP,SEP	1.0000	0.3314

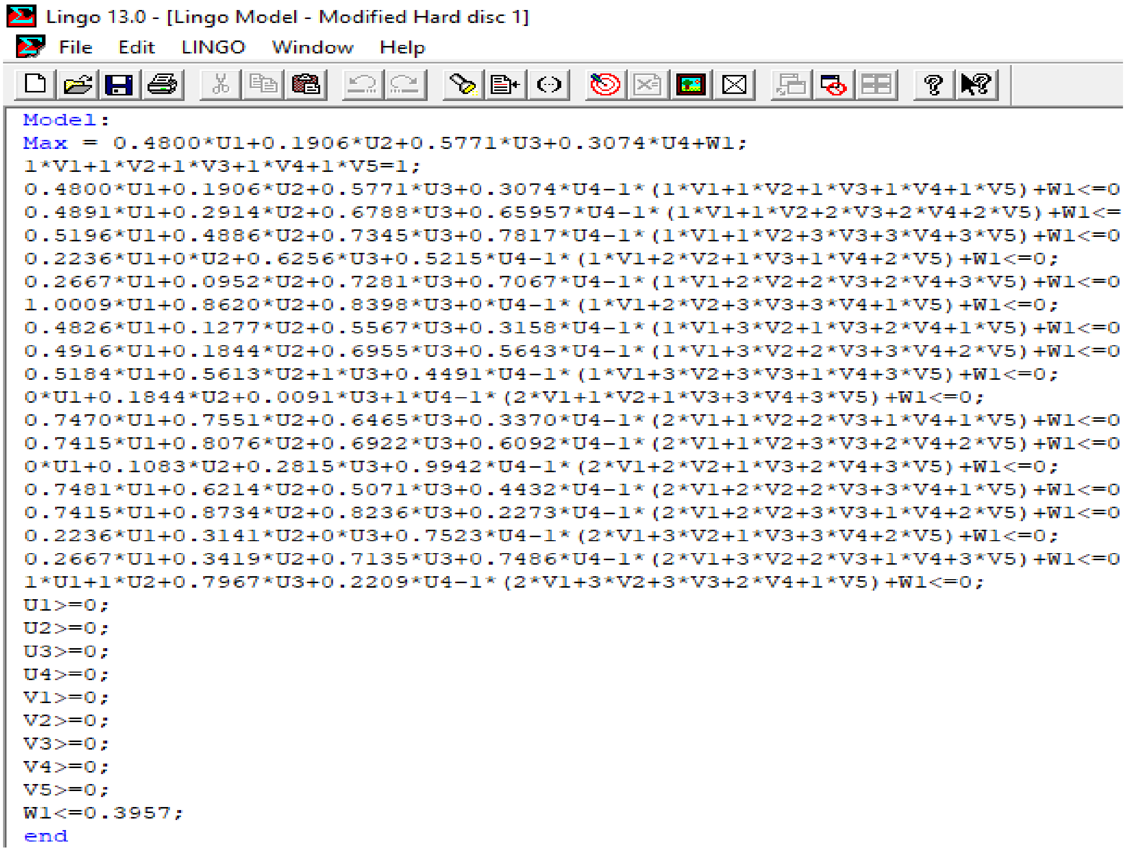


Figure 5. Lingo window showing the linear programming formulation for the modified VRS

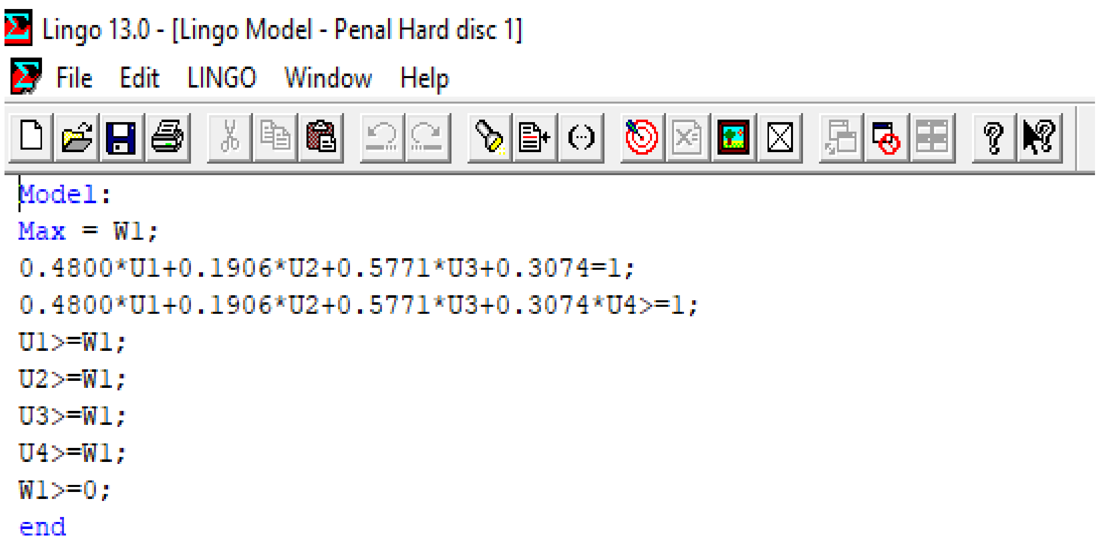


Figure 6. Lingo window showing the linear programming formulation for the VRS penalization coefficient

Table 3 shows the values of u_o^-, u_o^+ for efficient DMUs from where the upper bound restriction for the free variable ε, was obtained to be 0.3957. Table 4 contains the results of SN, NSN, θ, η, partitioning, modified VRS efficiency score and the penalization coefficient obtained for the 18 DMUs. Table 4 gives that at both orientations of DEA all the DMUs are efficient; hence all the efficient DMUs fall into EP and SEP. The proposed method criticizes and discriminates amongst the DMUs by correcting the menace associated with the standard model. With this, it was able to reveal those inefficient DMUs that have been returned as efficient by the standard VRS model. With this method, the efficiency of *DMUs 8* changes indicating that it is either a WEP or it compared with the WEP. This DMU was discarded because WEPs or its companion cannot yield an optimum output. Furthermore, *DMU 8* is not within the convex combination of the process design factors and did not show any possibility that virtual outputs can be formed from the process design factors level combination of this particular DMU. The second VRS DEA (Penalization coefficient) estimation yielded the highest score of 0.8379 for *DMU 10*. Figure 7 shows the response values for each factors level; hence using both the penalization coefficient and Figure 7 DMU *10* with $A_2B_1C_1D_3E_3$ was selected as the optimum factor level combination for the hard disc process according to the proposed method.

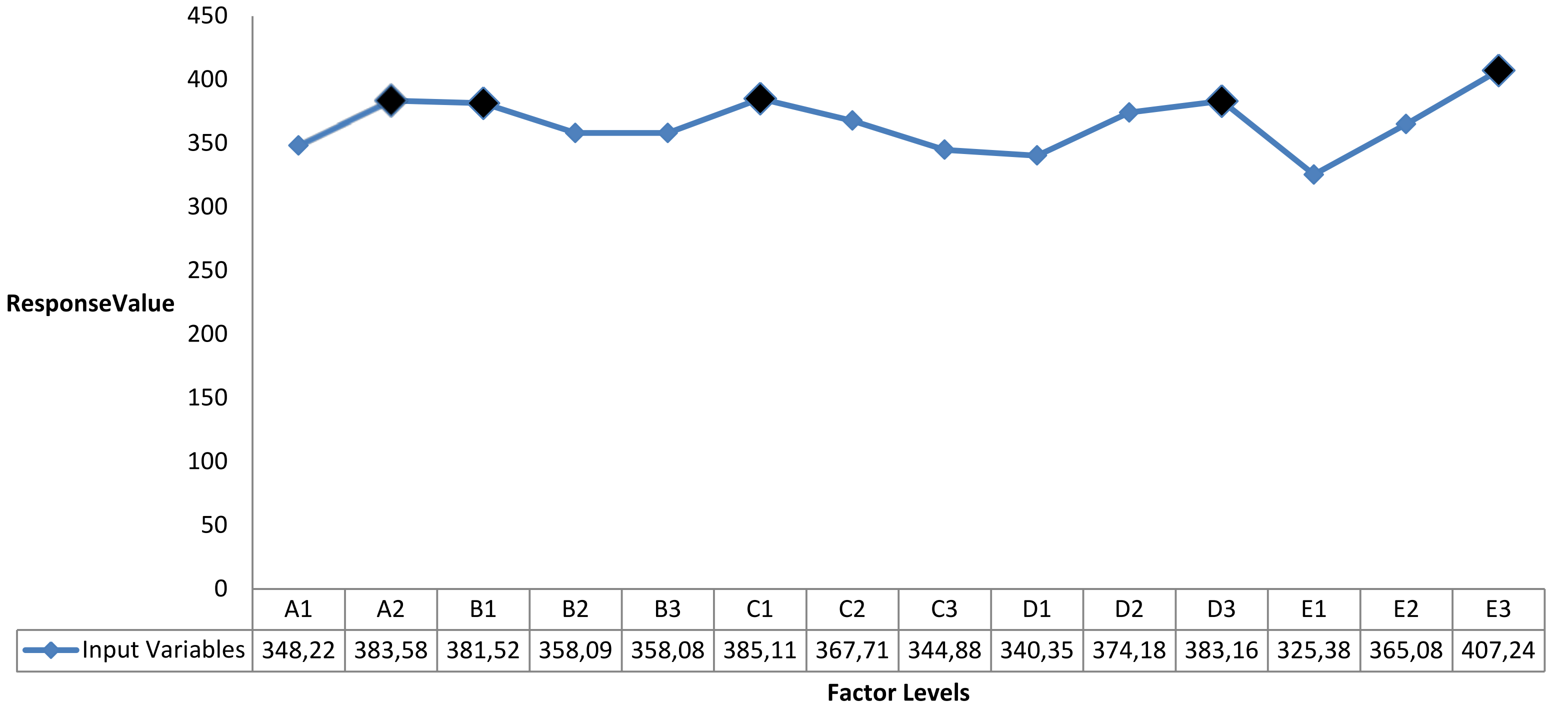


Figure 7. Optimal factors setting for hard disc drive using the proposed model (shaded points)

The same factor level combination was obtained from the benevolent formulation method of Al-Refaie and Al-Tahat (2011). To justify the efficacy of the proposed method over other methods previously applied, the anticipated improvement of the proposed method was obtained and compared with the anticipated improvement of BF of Al-Refaie and Al-Tahat (2011) and the PCA method of Su and Tong (1997) (see Table 5). This initial condition for hard disc obtained from the significant design factors as reported by Su and Tong (1997) was used for the calculation of the anticipated improvement. We used anticipated improvement to compare the proposed model with the previously used methods where the improvement made by each of the method over the initial condition of SN was evaluated. Therefore, we employ the similar mode of comparison and estimation that has been widely used and reported by Liao and Chen (2002), Al-Refaie and Al-Tahat, (2011), Su and Tong (1997); Al-Refaie, (2011 & 2012) where SN values were used to calculate the anticipated improvement. Furthermore, we compared the proposed model with the methods that have been used previously to analyze each case study. The improvement in each response is calculated as follows for optimal DMU;

$$\mathrm{PW} = -33.73 - (-36.28) = 2.55$$

$$\mathrm{PS} = -25.14 - (-21.48) = 0.34$$

$$\mathrm{OW} = -25.55 - (-31.51) = 2.96\mathrm{HFA} = 52.51 - (50.47) = 2.04$$

$$\text{Total anticipated improvement; } 2.55 + 0.34 + 2.96 + 2.04 = 10.890$$

In Table 5, the proposed method gave improvement value of 10.890 against BF technique which gave a value of 10.681, DEAR of 3.35 (see, e.g., Liao and Chan [2002, 825-837] on this important subject), and PCA of 2.61 (see, e.g., Su and Tong [1997, 406-416] on this important subject). This clearly attested to the fact that the proposed method is not only simple to adopt but it is simply effective, efficient and outperformed other mentioned methods that have been previously applied to solve multiple response problems in the robust parameter strategies for the hard disk drive studied.

Table 5. Summary of the anticipated improvement of previous methods and the proposed method for the hard disc case study

Response	Initial condition (1)	SN of the optimal combination obtained (2)				Anticipated improvement (2) - (1)			
		PCA (SU and Tong 1997)	DEAR (Liao and Chen 2002)	Benevolent Formulation (Al-Refaie and Al-Tahat (2011)	Proposed method (Modified VRS BPNN robust parameter)	PCA (SU and Tong 1997)	DEAR (Liao and Chen 2002)	Benevolent Formulation (Al-Refaie and Al-Tahat (2011)	Proposed method (Modified VRS BPNN robust parameter)
PW	-36.28	-33.740	-33.740	-33.730	-33.730	2.540	2.540	2.543	2.550
PS	-21.48	-19.370	-19.170	-21.050	-21.140	2.110	2.310	0.435	0.340
OW*	-31.51	27.710	28.970	-25.670	25.550	-3.800	-2.540	5.219	5.960
HFA	50.47	52.230	51.510	52.949	52.510	1.760	1.040	2.484	2.040
Total improvement anticipated						**2.610**	**3.350**	**10.681**	**10.890**

5.2 Optimizing gear hobbing operation

As previously demonstrated by Jeyapaul et al. 2006, the algorithm used to optimized gear hobbling operation with four quality responses namely left profile (LP) error, right profile (RP) error, left helix (LH) error and right helix (RH) error with six controllable factors which include the direction of gear hobbling (A), number of passes (B), source of hob (C), feed (D), speed (E) and job run out (F). The input and response data of gear hobbling as further analyzed by BF and reported by Al-Refaie and Al-Tahat (2011) is presented in Table 6. Factors A, B and C are at two levels each, factors D, E and F are at three levels each. Factors B and C are assigned to the same column as BC to make up a modified L_{18} orthogonal (OA) array. The modified OA can, therefore, hold three-level factors in its first three column and three-level factors in the next three columns (see, e.g., Jeyapaul et al. [2006, 870-878] on this concept of modified OA for this particular case study). A total of 18 parameter level combinations were achieved therefore a modified L_{18} orthogonal array was also adopted for the robust parameter procedure. By using the input and output weight evaluated, the upper bound variable ε restriction according to the experimental data is obtained as 0.8915 (Table 7)

Table 6. Input and output data gear hobbing operation case study

DMU	Process parameter setting (Input Variables)					Responses (Output Variables)			
	A	BC	D	E	F	LP	RP	LH	RH
1	1	1	1	1	1	72.53	73.97	47.37	42.90
2	1	1	2	2	2	75.67	74.23	32.43	39.10
3	1	1	3	3	3	74.20	73.10	51.93	51.10
4	1	2	1	1	2	74.80	77.03	61.27	55.03
5	1	2	2	2	3	75.37	75.93	82.97	59.80
6	1	2	3	3	1	71.83	73.93	35.83	42.30
7	1	3	1	2	1	75.10	71.97	54.47	60.07
8	1	3	2	3	2	77.03	74.80	56.17	44.90
9	1	3	3	1	3	77.63	72.27	57.87	59.83
10	2	1	1	3	3	73.67	76.80	42.33	47.10
11	2	1	2	1	1	74.23	79.03	48.83	34.20
12	2	1	3	2	2	71.97	75.37	42.03	30.77
13	2	2	1	2	3	75.10	74.53	34.17	34.73
14	2	2	2	3	1	76.50	74.50	40.33	37.83
15	2	2	3	1	2	72.83	74.77	42.33	40.37
16	2	3	1	3	2	75.63	78.73	45.17	35.27
17	2	3	2	1	3	75.40	77.07	42.93	39.27
18	2	3	3	2	1	75.90	72.00	50.90	47.40

Table 7. Input and output weight obtained from the input orientation of the standard VRS models for gear hobbing operation

A	B	C	D	E	F	LP	RP	LH	RH	u_o
1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-1.000
0.842	0.158	0.000	0.000	0.000	0.000	1.091	0.811	0.000	0.000	0.000
0.071	0.545	0.128	0.000	0.000	0.000	0.653	0.000	0.552	0.041	-0.419
1.000	0.000	0.000	0.000	0.000	0.000	0.000	1.377	0.000	0.000	0.000
0.128	0.035	0.000	0.000	0.267	0.000	0.000	0.164	0.906	0.000	0.000
1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-1.000
0.000	0.284	0.011	0.000	0.136	0.000	0.000	0.000	0.000	1.129	0.129
0.283	0.000	0.000	0.116	0.184	0.000	0.935	0.385	0.000	0.000	0.000
0.047	0.283	0.000	0.103	0.000	0.000	0.800	0.000	0.324	0.000	0.000
0.279	0.443	0.000	0.000	0.000	0.000	0.000	0.908	0.000	0.581	0.000
0.425	0.151	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000
0.240	0.216	0.000	0.000	0.000	0.304	0.000	1.199	0.000	0.000	-0.409
0.010	0.290	0.140	0.008	0.000	0.243	1.213	0.815	0.000	0.000	0.000
0.251	0.137	0.000	0.000	0.225	0.000	1.040	0.423	0.000	0.000	0.000
0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	-1.000
0.460	0.000	0.080	0.000	0.000	0.000	0.000	1.972	0.000	0.000	0.892
0.336	0.000	0.000	0.000	0.145	0.183	0.000	1.367	0.000	0.000	0.000
0.000	0.108	0.000	0.041	0.196	0.101	0.565	0.000	0.175	0.358	-0.127

Table 8. The values of u_o^-, u for efficient DMUs for the gear hobbing operation case study

DMUs	u_o^-	u_o^+
1	0.0000	1.0000
2	0.0000	1.0000
3	0.0000	1.0000
4	0.0000	1.0000
5	0.0000	1.0000
6	0.0000	1.0000
7	0.1292	1.0000
8	0.0000	1.0000
9	0.0000	1.0000
10	0.0000	1.0000
11	0.0000	1.0000
12	0.4085	1.0000
13	0.0000	1.0000
14	0.0000	1.0000
15	1.0000	1.0000
16	0.8915	1.0000
17	0.0000	1.0000

$\varepsilon = \text{Max } u_o^+/u_o^- \neq 1 = 0.8915$

At the input orientation of DEA Table 9, *DMUs 1-17* were efficient with *DMU 18* as inefficient. Similarly, on output orientation, *DMU 6, 15 and 18* are inefficient while others were on the frontier. From the partitioning, *DMUs 1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12, 13, 14, 16, and 17* are EPs and SEPs while *DMUs 6, 15* and *18* are WEPs. On the application of the proposed modified VRS model, *DMUs 6, 15,* and *18* were again returned as inefficient. With this, *DMUs 6, and 15* are strictly WEP *and because DMU 18* was inefficient at both orientations and also with the modification then *DMU 18* is strictly inefficient and cannot be said to be in the same possible production set (PPS) or in *DMU 18* is not within the convex combination of the controllable factors for this gear hobbling operation.

Table 9. Efficiency scores for the standard orientations, modified BCC model and the penalization coefficient for gear hobbing case study

	Design factors (Input Variables)					Robust Parameter												
						Normalized Signal-to-Noise ratio				Signal-to-Noise ratio				VRS Modified Model				
DMU	**A**	**BC**	**D**	**E**	**F**	**LP**	**RP**	**LH**	**RH**	LP	RP	LH	RH	**Score (θ)**	**Score (η)**	**Partitioning**	**Modified**	**Penalization Coefficient**
1	1	1	1	1	1	0.1249	0.2929	0.4034	0.4968	-37.21	-37.38	-33.51	-32.65	1.0000	1.0000	EP, SEP	1.0000	0.7587
2	1	1	2	2	2	0.6707	0.3304	0.0000	0.3581	-37.58	-37.41	-30.22	-31.84	1.0000	1.0000	EP, SEP	1.0000	0.7357
3	1	1	3	3	3	0.4180	0.1665	0.5012	0.7582	-37.41	-37.28	-34.31	-34.17	1.0000	1.0000	EP, SEP	1.0000	0.5423
4	1	2	1	1	2	0.5218	0.7261	0.6773	0.8690	-37.48	-37.73	-35.74	-34.81	1.0000	1.0000	EP, SEP	1.0000	0.3579
5	1	2	2	2	3	0.6195	0.5724	1.0000	0.9933	-37.54	-37.61	-38.38	-35.53	1.0000	1.0000	EP, SEP	1.0000	0.3139
6	1	2	3	3	1	0.0000	0.2871	0.1061	0.4757	-37.13	-37.38	-31.08	-32.53	1.0000	0.9803	WEP	0.9978	
7	1	3	1	2	1	0.5733	0.0000	0.5520	1.0000	-37.51	-37.14	-34.72	-35.57	1.0000	1.0000	EP, SEP	1.0000	0.4705
8	1	3	2	3	2	0.9001	0.4122	0.5847	0.5649	-37.73	-37.48	-34.99	-33.04	1.0000	1.0000	EP, SEP	1.0000	0.4062
9	1	3	3	1	3	1.0000	0.0445	0.6165	0.9940	-37.80	-37.18	-35.25	-35.54	1.0000	1.0000	EP, SEP	1.0000	0.3766
10	2	1	1	3	3	0.3257	0.6941	0.2836	0.6364	-37.35	-37.71	-32.53	-33.46	1.0000	1.0000	EP, SEP	1.0000	0.5155
11	2	1	2	1	1	0.4233	1.0000	0.4357	0.1580	-37.41	-37.96	-33.77	-30.68	1.0000	1.0000	EP, SEP	1.0000	0.4957
12	**2**	**1**	**3**	**2**	**2**	**0.0251**	**0.4933**	**0.2760**	**0.0000**	**-37.14**	**-37.54**	**-32.47**	**-29.76**	**1.0000**	**1.0000**	**EP, SEP**	**1.0000**	**1.2588**
13	2	2	1	2	3	0.5733	0.3735	0.0556	0.1810	-37.51	-37.45	-30.67	-30.81	1.0000	1.0000	EP, SEP	1.0000	0.845
14	2	2	2	3	1	0.8112	0.3692	0.2321	0.3088	-37.67	-37.44	-32.11	-31.56	1.0000	1.0000	EP, SEP	1.0000	0.5809
15	2	2	3	1	2	0.1780	0.4079	0.2836	0.4059	-37.25	-37.47	-32.53	-32.12	1.0000	0.5319	WEP	0.94921	
16	2	3	1	3	2	0.6639	0.9594	0.3527	0.2040	-37.57	-37.92	-33.10	-30.95	1.0000	1.0000	EP, SEP	1.0000	0.4587
17	2	3	2	1	3	0.6246	0.7316	0.2986	0.3646	-37.55	-37.74	-32.66	-31.88	1.0000	1.0000	EP, SEP	1.0000	0.4952
18	2	3	3	2	1	0.7098	0.0045	0.4799	0.6459	-37.60	-37.15	-34.13	-33.52	0.8429	0.8504	Inefficient	0.8429	

The second DEA, penalization coefficient gave the highest score of 1.2588 for *DMU 12* and couple with Figure 8 the response values for each factors level DMU *12* with $A_2B_1C_1D_3E_2F_2$ is selected as the optimum factor level combination. The same level combination was also obtained with benevolent formulation approach. However in Table 10, with the initial condition done based on the significance of the factors as determined by the engineering judgment the anticipated improvement of the proposed method was obtained and compared with GA (see e.g., Jeyapaul *et al.*, [2006, 870-878] on this selection) and BF, of Al-Refaie and Al-Tahat (2011) other methods with an improvement value of 11.8224 against BF of 11.2506 and GA of 4.1498. Therefore, the proposed model was concluded more effectually than BF and GA for the gear hobbing operation studied.

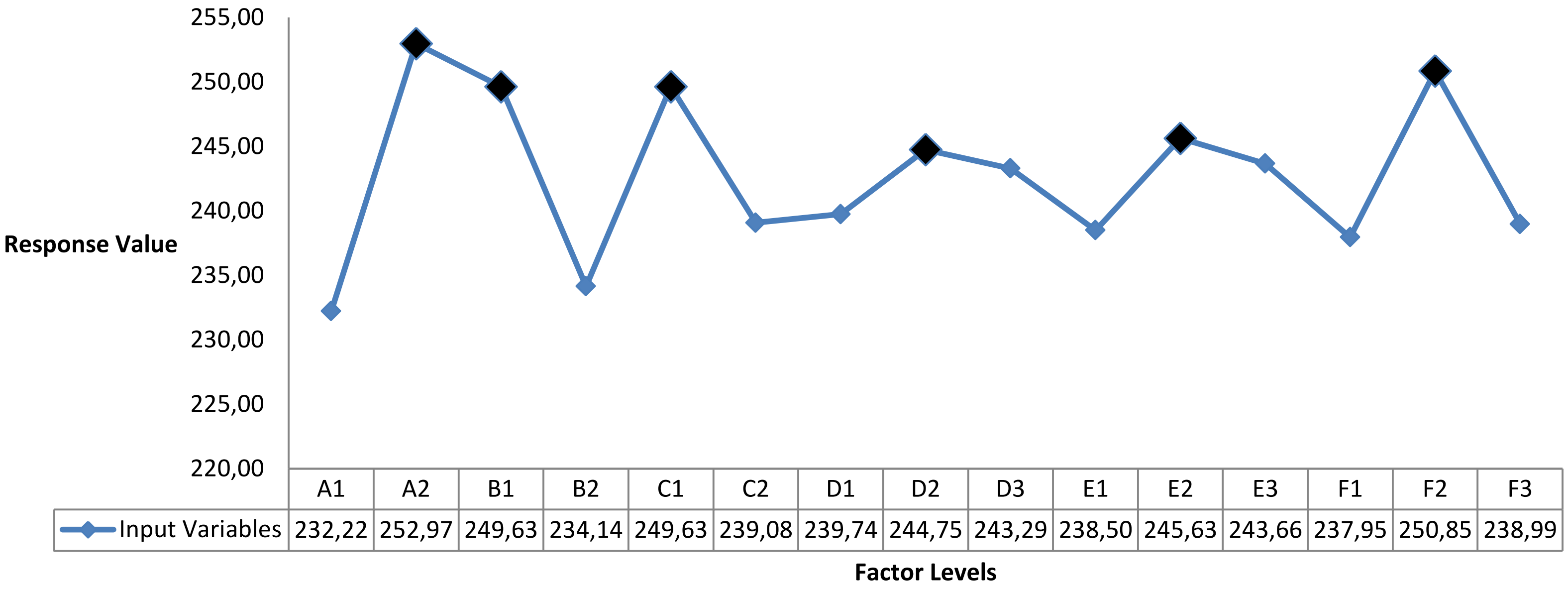


Figure 8. Optimal factors setting for gear hobbing operation using the proposed model (shaded points)

Table 10. Summary of the anticipated improvement of previous methods and the proposed method for the gear hobbing case study

Response	**Initial condition (1)**	**SN of the optimal combination obtained (2)**				**Anticipated improvement (2) - (1)**			
		Generic Algorithm (Jeyapaul *et al.*, 2006)	Benevolent Formulation (Al-Refaie and Al-Tahat (2011)		Proposed method (Modified VRS BPNN robust parameter)	Generic Algorithm (Jeyapaul *et al.*, 2006)	Benevolent Formulation (Al-Refaie and Al-Tahat (2011)		Proposed method (Modified VRS BPNN robust parameter)
LP error	-37.8581	-37.4917	-37.3728	-37.1800	-37.1400	0.3664	0.4853	0.6781	0.7181
RPerror	-37.4952	-37.4045	-37.7724	-37.4984	-37.5400	0.0907	-0.2772	-0.0032	-0.0443
LHerror	-36.6009	-34.4082	-31.9040	-31.4320	-31.4320	2.1927	4.6968	5.1688	5.1689
RHerror	-35.7397	-34.2396	-29.9858	-30.3328	-29.7600	1.5001	5.7539	5.4069	5.9797
Total improvement anticipated						**4.1498**	**10.6588**	**11.2506**	**11.8224**

5.3 Quality dried apple

Discala *et al.*, (2013) demonstrated ANN-GA to predict the quality characteristics of apple during convective dehydration where hot air flow was at three different temperatures of 40 ^{o}C, 60 ^{o}C and 80 ^{o}C and at three air flow-rates of 0.5m/s, 1m/s and 1.5m/s. The quality characteristics examined were total phenolic content (TPC), surface colour (SC) and water holding capacity (WHC). The uncertainty was given in terms of the correlation coefficient r^2 of 0.987 for SC, 0.990 for TPC and 0.994 for WHC. A total of 9 parameters level settings existed; therefore L_9 orthogonal array was adopted for the robust parameter procedure and 9 neurons were used at the hidden layer. Signal-to-Noise ratios (SNs) were obtained and normalized (NSNs) accordingly. The upper bound variable restriction was estimated from the estimated input and output weights presented in Table 11 to be 0.6013 (Table 12).

Table 11. Input and output weight obtained from the input orientation of the standard VRS models for apple dehydration

DMU	Score	Weight (Air drying Temperature)	Weight (Air drying velocity)	Weight (Surface colour)	Weight (Total Phenol)	Weight (Water Holding capacity)	u_o
1	1.0000	0.0250	0.0000	0.7221	1.5040	0.0000	0.0000
2	1.0000	0.0250	0.0000	0.0000	0.0000	1.0000	0.0000
3	1.0000	0.0250	0.0000	1.2870	0.0000	0.0000	0.0000
4	1.0000	0.0167	0.0000	0.0000	1.2860	0.0000	0.0000
5	1.0000	0.0167	0.0000	0.0000	1.0540	0.2785	0.0000
6	0.7426	0.0167	0.0000	0.7763	1.1770	0.0000	0.2700
7	1.0000	0.0125	0.0000	0.5822	0.8824	0.0000	0.2025
8	1.0000	0.0125	0.0000	0.0000	1.1230	0.0000	0.1231
9	1.0000	0.0125	0.0000	0.1033	1.3360	0.0000	0.3356

Table 12. The values of u_o^-, u_o^+ for the efficient DMUs of Apple dehydration case study

DMUs	$\boldsymbol{u_o^-}$	$\boldsymbol{u_o^+}$
1	0.5547	0.5547
2	0.0000	0.0000
3	0.1549	0.1549
4	0.6013	0.6013
5	0.2531	0.2531
7	0.0000	0.0000
8	0.4412	0.4412
9	0.0000	0.0000

$$\varepsilon = \mathrm{Max}\, \mathrm{u}_\mathrm{o}^{+}/\mathrm{u}_\mathrm{o}^{-} \neq 1 = 0.6013$$

The partitioning revealed in Table 13, that *DMU 6* is strictly inefficient while others are efficient. Interestingly, the proposed method revealed contrary results that DMU 6 is efficient and *DUMs 5, 8* and *9* are inefficient. By implication, standard VRS models would have discarded *DMU 6* and accepted *DUMs 5, 8* and *9* hereby misleading the quality engineer or production manager to treat them as efficient DMUs and include them in the search for the optimum factor level setting. The modified VRS model has through enhanced discrimination corrected the problem associated with the standard models. On the application of the penalizing DEA model, *DMU 8* gave the highest penalization coefficient of 0.8905 and is selected. With Figure 9 which presents the response values for each factors level and the penalization coefficient obtained, the optimal factor level setting is selected to be at the temperature of 80 ^{o}C and at air flow rate at 0.5 m/s for the apple dehydration process.

This connotes that at the higher temperature at 80 ^{o}C and at lower air flow rate 0.5m/s will favour all the quality attributes. This assertion corroborated the findings of Discala *et al.*, 2013 where (i) lowest surface colour change was noticed at 80 ^{o}C at all flow rates (0.5, 1 and 1.5 m/s), (ii) TPC degradation decreased with increasing temperature at air flow rates 0.5 and 1 m/s and pointed out specifically that at 80 ^{o}C, degradation of TPC was the lowest and (iii) WHC changes as air temperature increased at constant air flowrate. Considering the values of WHC, 48.28 also show that dehydrating apple at this constant air rate would retain a large amount of water. The anticipated improvement, Table 14, shows that the proposed model gave the higher value of 16.989 over that of GA which is 1.284 obtained according to the approach of Discala *et al.*, (2013).

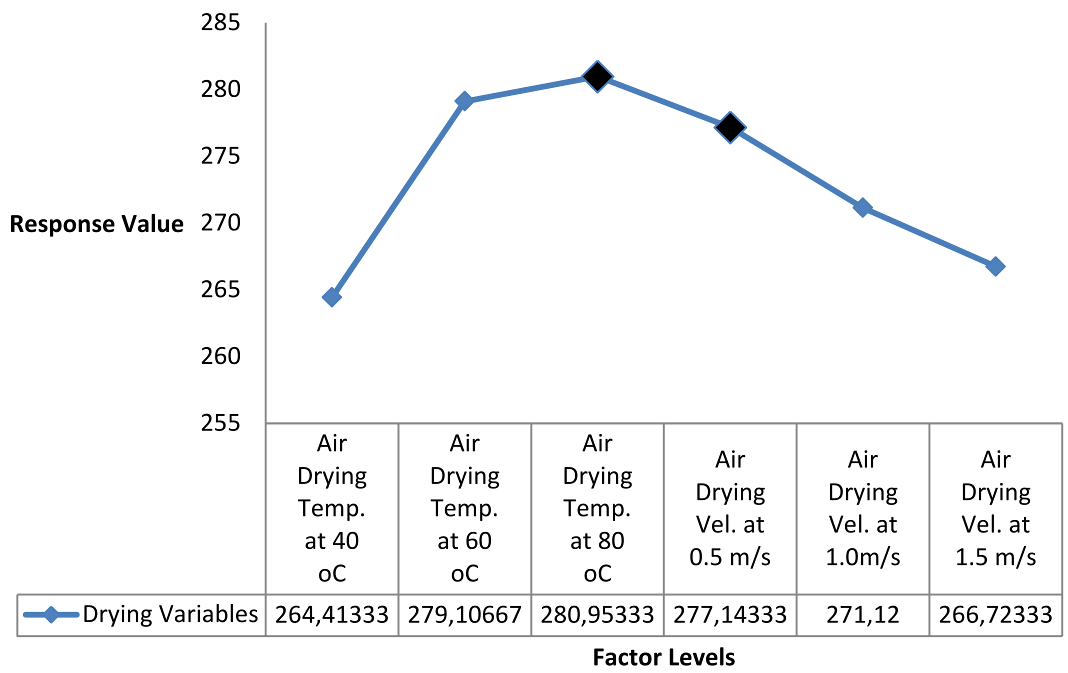


Figure 9. Optimal factors setting for apple dehydration (drying) using the proposed model (shaded points)

Table 13. Efficiency scores for standard orientations, modified BCC model and penalization coefficient for apple dehydration

			Robust Parameter						**VRS Modified Model**				
	Design factors (Input Variables)		**Normalized Signal-to-Noise ratio**			**Signal-to-Noise ratio**							
DMU	**Air drying Temperature**	**Air drying velocity**	**SC**	**TPC**	**WHC**	**SC**	**TPC**	**WHC**	**Score (θ)**	**Score (η)**	**Partitioning**	**Modified**	**Penalization**
1	40.000	0.500	0.731	0.314	0.126	-31.056	30.084	33.160	1.000	1.000	EP,SEP	1.000	0.854
2	40.000	1.000	0.496	0.004	1.000	-29.278	28.752	35.010	1.000	1.000	EP,SEP	1.000	0.667
3	40.000	1.500	0.777	0.000	0.590	-31.403	28.736	34.141	1.000	1.000	EP,SEP	1.000	0.732
4	60.000	0.500	0.458	0.777	0.647	-28.989	32.074	34.263	1.000	1.000	EP,SEP	1.000	0.5314
5	60.000	1.000	0.488	0.735	0.809	-29.215	31.890	34.606	1.000	1.0000	EP,SEP	0.742	
6	60.000	1.500	0.670	0.418	0.000	-30.599	30.532	32.893	0.743	0.797	WEP	1.000	0.482
7	**80**.000	**0.500**	**1.000**	**0.703**	**0.370**	**-33.093**	**31.754**	**33.675**	**1.000**	**1.000**	**EP,SEP**	**1.000**	**0.891**
8	80.000	1.000	0.000	1.000	0.123	-25.525	33.029	33.153	1.000	1.000	EP,SEP	0.934	
9	80.000	1.500	0.412	0.968	0.329	-28.640	32.893	33.589	1.000	1.000	EP,SEP	0.934	

Table 14. Summary of the anticipated improvement of previous and proposed method for the apple

		SN of the optimal combination obtained (2)		**Anticipated improvement (2) - (1)**	
Response	**Initials Condition (1)**	Genetic Algorithm (Discala *et al.*, 2013)	Proposed method (Modified VRS BPNN robust parameter)	Genetic Algorithm (Discala et al., 2013)	Proposed method (Modified VRS BPNN robust parameter)
SC	38.651	28.422	33.093	-10.229	-5.558
TPC	-43.988	-32.475	-31.754	11.513	12.234
WHC	-34.255	-34.255	-33.675	0.000	10.313
		Total improvement anticipated		**1.284**	**16.989**

This case study is used to demonstrate how BPNN can be used in predicting the values of the responses beyond the experimented input variables. The experimental data was used to train and validate the BPNN using trial and error search technique and it revealed that hidden layer containing nine (9) neurons gave the lowest EMS and highest regression coefficient r^2. The adequacy of the topology adopted was shown in Table 15 having the lowest EMS and the highest regression coefficient *R*-value of 0.000338 and 0.999 for the training respectively, and this is also supported by the cross-validation with the *R*-value of 0.998 and EMS of 10.306.

Table 15. Trial and Error for determining the number of neuron in the hidden layer

Number of Neuron	Training		Cross Validation	
	EMS	R^2	EMS	R^2
1				
2	81.740	0.790	9.680	0.984
3	8.020	0.954	5.580	0.987
4	38.810	0.780	5.180	0.999
5	87.020	0.486	15.110	0.981
6	87.670	0.559	10.570	0.964
7	0.810	0.996	41.570	0.896
8	221.910	0.341	27.080	0.686
9	0.0003	0.999	10.310	0.998
10	2.400	0.985	5.960	0.995
11	161.110	0.564	523.700	0.043
12	9.020	0.950	181.380	0.765
13	154.680	0.679	23.030	0.983
14	2.440	0.989	138.660	0.726
15	3.226E-26	1.000	170.830	-0.550

This well-trained topology can be used to estimate within acceptable error limits, the multi-quality response of any process parameter settings beyond those experimentally tested. Going by the results obtained, our study suspected that the fractional factorial number of the orthogonal array obtained could be used as the number of neurons in the hidden layer for solving this kind of problem in the robust parameter strategy. Table 16 presents the demonstration output using the selected BPNN to predict response value from the input variables covered in the experiment and should response is sought for another set of input variables outside those covered by the experiment.

Table 16. BPNN demonstration of the predicted response

Experimental data					BPNN Predicted response		
Input Variables		Response					
Air drying Temperature	Air drying velocity	Surface colour	Total Phenol	Water Holding capacity	Surface colour	Total Phenol	Water Holding capacity
40.00	0.50	35.71	31.93	45.50	35.71±0.0014	31.71±5.7e-4	45.15±3.3e-4
40.00	1.00	29.10	27.39	56.30	30.012±0.9190	26.87±0.5227	50.84±5.4590
40.00	1.50	37.17	27.34	50.94	37.16±0.0073	27.34±0.0033	50.94±5.4e-4
60.00	0.50	28.15	40.15	51.66	28.16±0.0093	40.14±0.0087	51.68±0.0190
60.00	1.00	28.89	39.31	53.74	28.92±0.0283	39.32±0.0083	53.72±0.0215
60.00	1.50	33.88	33.62	44.12	33.88±0.0016	33.65±0.029	44.08±0.0414
80.00	0.50	45.15	38.70	48.28	45.15±0.0034	38.72±0.0174	48.27±0.0096
80.00	1.00	18.89	44.82	45.46	18.96±0.0450	44.81±0.0100	45.47±0.006
80.00	1.50	27.04	44.12	47.80	53.448±26.408	50.23±6.108	49.24±1.443

5.4 Integrated data envelopment-thermoexergetic optimization framework for multicomponent distillation system

Case study for this research is an exergy analysis of a multicomponent distillation system described by Perry and Green (1997). An HYSYS simulation was adopted and the separation was arranged sequentially according to heuristics of the multicomponent mixture as proposed by Adesina and Popoola, 2016. The specifications of the first column with 5% propane, 15% iso-butane, 25% n-butane, 20% iso-pentane and 35% n-pentane (See e.g Perry and Green [1997, 13:37-43] on the complete description of these specifications) tagged the base case include feed temperature of -50^{o}C, feed pressure of 1000KPa, and reflux ratio of 4. The model was for a total condenser, the simulation was carried out for these initial specifications and was used to generate the temperature, pressure, specific enthalpy, and specific entropy and flow rates for every stream in and out of each column; the tray by tray temperature, pressure and specific enthalpy were equally obtained. Thermodynamic data were extracted. The specific enthalpy and entropy for the tray by tray vapour and liquid phase at reference (environmental conditions) temperature of 293K and pressure of 101.3KPa were obtained. The profiles of the exergetic efficiency and the destruction distribution rate are used to determine the thermo-feasible systems. The profiles are a plot of each thermo-response against the number of trays in each column. For the simulation sensitivity, the temperature range considered was -30 ^{o}C and -80 ^{o}C, pressure 800 kPa and 1200 kPa and reflux ratio and 2 and 6 and 50% split feed was considered. Therefore, the main intended contribution of the study is in two-fold. First, unlike the previous efforts that utilized RSM a parametric technique, we employ integrated thermoexergetic-nonparametric data envelopment in the robust SN procedures. Secondly, we revamped VRS facet robust parameter framework by imposing partitioning within the facet VRS and also ensure self-evaluation in order to improve its discriminatory tendency.

Furthermore, it should be clarified that simulation is only used for this case study to determine various data needed for the proposed model – the process responses. It is used to replace experimentation as itemized in Phase A of the proposed model. Simulation simply means the substitution of physical experimentation to a virtual component (software) on the computers to compute the results of some physical phenomenon (models). Once the mathematical models that describe all the parameters of physical model to represent physical model in virtual form are built, then conditions are applied as if physical experiment is to be done. In this way actual experimentation can be avoided. According to NSF (2006), steadily increase and widely acceptance of simulation applications is due to the fact that (i) simulations are cheaper, safer and sometimes more ethical than conducting real-world experiments (ii) Simulations can even be more realistic than traditional experiments because the experimenter is allowed to freely configure the environment parameters found in the operational application field of the anticipated process or product (iii) Simulations faster than real time. By and large it is technologically correct to simulate.

The exergy balance for the open system at steady state for was given by equations 14-15 according to Jean-Francois *et al*., (2008);

$$Ex_{PH} = (H - T_0 S) - (H_0 - T_0 S_0) \tag{14}$$

The exergetic efficiency for a real column is written;

$$\psi = \frac{\dot{E}x_{distillate} + \dot{E}x_{bottom} + \left(1 - \frac{T_O}{T_{cond}}\right)\dot{Q}_{cond}}{\dot{E}x_{feed} + \left(1 - \frac{T_O}{T_{reboiler}}\right)\dot{Q}_{reboiler}} \tag{15}$$

Where;

$$\mathrm{T_{Cond}} = \mathrm{T_{distillate}} - \mathrm{T_{Cond\ diff}} \tag{16}$$

$$\mathrm{T_{Cond\ diff}} = \frac{\mathrm{T_{cooling\ water\ in}} + \mathrm{T_{cooling\ water\ out}}}{2} \tag{17}$$

$$\mathrm{T_{reboiler}} = \mathrm{T_{distillate}} - \mathrm{T_{reboiler\ diff}} \tag{18}$$

$$\mathrm{T_{reboiler\ diff}} = \frac{\mathrm{T_{cooling\ water\ in}} + \mathrm{T_{cooling\ water\ out}}}{2} \tag{19}$$

T_{Cond} is the condenser temperature, $T_{Cond\ diff}$ is the average temperature of both the cooling water inlet and outlet at the condenser, $T_{reboiler\ diff}$ is the average temperature of both the cooling water inlet and outlet at the reboiler, and $T_{reboiler}$ is the temperature difference between distillate reboiler temperature difference. The exergy loss balance for open systems at steady state can be obtained as

$$\mathrm{Ex_{lost}} = \mathrm{Ex_{in}^{liquid}} + \sum \mathrm{Ex_{feed}} - \mathrm{Ex_{out}^{vapour}} + \mathrm{Ex_{out}^{liquid}} + \sum \mathrm{Ex_{side}} + \mathrm{Q}\left(1 - \frac{\mathrm{T_o}}{\mathrm{T_{heat}}}\right) \qquad (20)$$

The method of solution of Fenske-Underwood-Gillard (FUG) was anticipated. The reason is that this combination relates the actual column performance to total and minimum reflux conditions for separating between two key components and it is the most convenient in setting the reflux ratio-minimum reflux (See e,g Perry and Green, [1997, 13:37-43] for detail explanation of this concept). However, the separation of the mixture into components is carried out using Hyprotech System Simulator (HYSYS) version 3.2. Here, we employed Equation of State (EOS) as the thermodynamic model and Peng-Robinson (PR) was selected in the property package and filtered accordingly with the property package filter. The choice of PR was due to its ability to adequately handle hydrocarbon separation, provide large temperature and pressure ranges offer the largest binary interaction parameter database. The adapted framework for the proposed integrated model is depicted in Figure 10.

For the robust SN; the experiment has three control factors: A-temperature (^oC), B-pressure (KPa), C-reflux ratio and one noise factor is the environmental condition of (ambient) temperature. The process thermo-responses are the system exergy efficiency (%) with the quality attribute of larger-the-better (LTB) and exergy loss rate (kJ/hr) with the quality attribute of Smaller-The-Better (STB). Temperature and pressure are at three levels each while reflux ratio is at two levels. The exergy experiment was conducted for high and low levels of the noise factor.

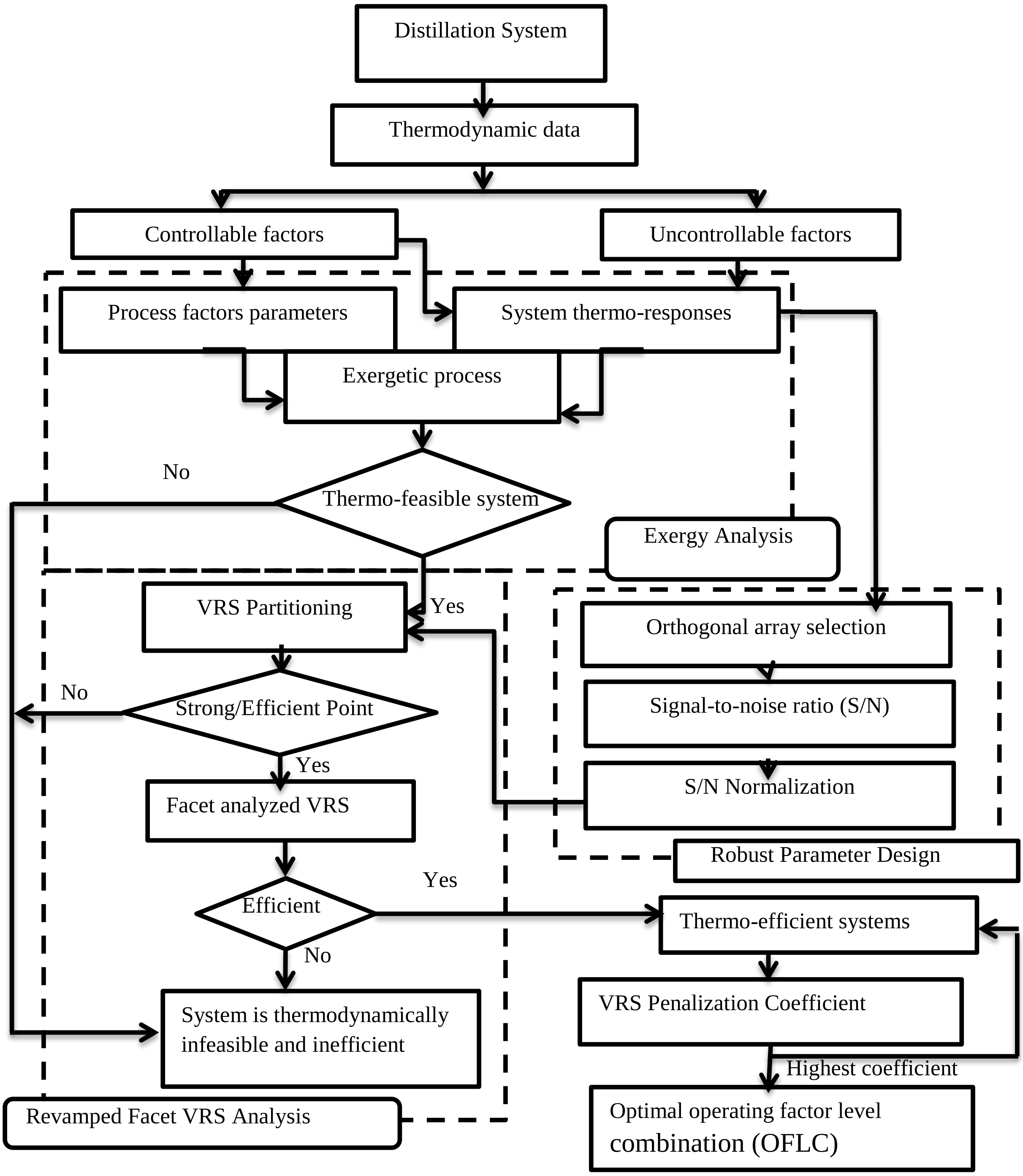


Figure 10. The integrated framework adapted from the proposed model

Figure 11 represents the optimum sequence as obtained by a converged HYSYS simulation. The Depropanizer consist of 55 trays with feed tray on 19. Debutanizer consist of 62 trays with feed tray was on tray 31. Figures 12-13 results show that pure separation of the component was obtained. The result also shows that the composition of propane was vaporized at the feed inlet position located on tray 19. The problem of the degree of freedom for the separations was solved by varying the reflux ratio as 2, 4, 6, we also set the convergence of the HYSYS simulation to the recovery of 99% of the pure component at the overhead and we specified the total condenser and reboiler so that the number of the variables can be increased by the variables and equations for the liquid and vapour delivering rates. Fig. 13 shows that iso-butane and n-butane got vaporized and separated to the top of the column as distillate leaving iso-pentane and n-pentane as the liquid to the bottom of the column. Iso-butane and n-butane were separated by butane splitter component. Similarly, iso-pentane and n-pentane were separated by pentane component splitter. The exergetic and exergetic destruction profiles for the columns are obtained. For the robust SN; a total of 18 thermo-feasible combinations were obtained from exergy analysis. Therefore L_{18} orthogonal array was used for the robust design. Signal-to-Noise ratios (SNs) were obtained, normalized (NSNs) accordingly and the presented in Table 17.

Table 17. Signal-Noise ratio (SN) and Normalized signal to noise ratio (NSN) for the Multicomponent distillation case study 1

DMU	**Signal-to-Noise ratio**		**Normalized Signal-to-Noise ratio**	
	Exergy Efficiency (%)	**Exergy Loss Rate (kJ/hr)**	**Exergy Efficiency**	**Exergy Loss Rate**
01	35.3772	-1.51E+02	0.094	0.945
02	39.61824	-1.24E+02	0.958	0.081
03	35.29398	-1.52E+02	0.077	0.958
05	38.05963	-1.43E+02	0.640	0.691
07	37.52667	-1.53E+02	0.532	1.000
09	37.85969	-1.44E+02	0.600	0.722
10	39.00535	-1.36E+02	0.833	0.465
11	39.20751	-1.34E+02	0.874	0.400
16	38.35851	-1.41E+02	0.701	0.613
18	39.37806	-1.32E+02	0.909	0.332
19	35.49034	-1.51E+02	0.117	0.946
21	35.32826	-1.51E+02	0.084	0.957
23	38.0618	-1.43E+02	0.641	0.691
27	38.77039	-1.38E+02	0.785	0.529
28	35.37572	-1.51E+02	0.093	0.945
29	39.82364	-1.21E+02	1.000	0.000
30	38.32697	-1.41E+02	0.695	0.613
36	34.9171	-1.53E+02	0.000	1.007

Table 18. The values of u_o^-, u_o^+ for efficient DMUs for multicomponent distillation case

DMUs	u_o^-	u_o^+
01	1	1
02	1	1
03	0.972	1
07	0.1034	0.1034
09	4.821	4.821
10	8.523	8.523
11	8.381	8.381
16	0.000	1
18	7.526	7.526
19	0.000	1
21	0.972	1
23	5.054	5.054
27	5.058	5.058
28	1	1
29	1	1
30	5.764	5.764
36	0.806	0.806

$\varepsilon = Max\, u_o^+/u_o^- \neq 1 = 0.972$

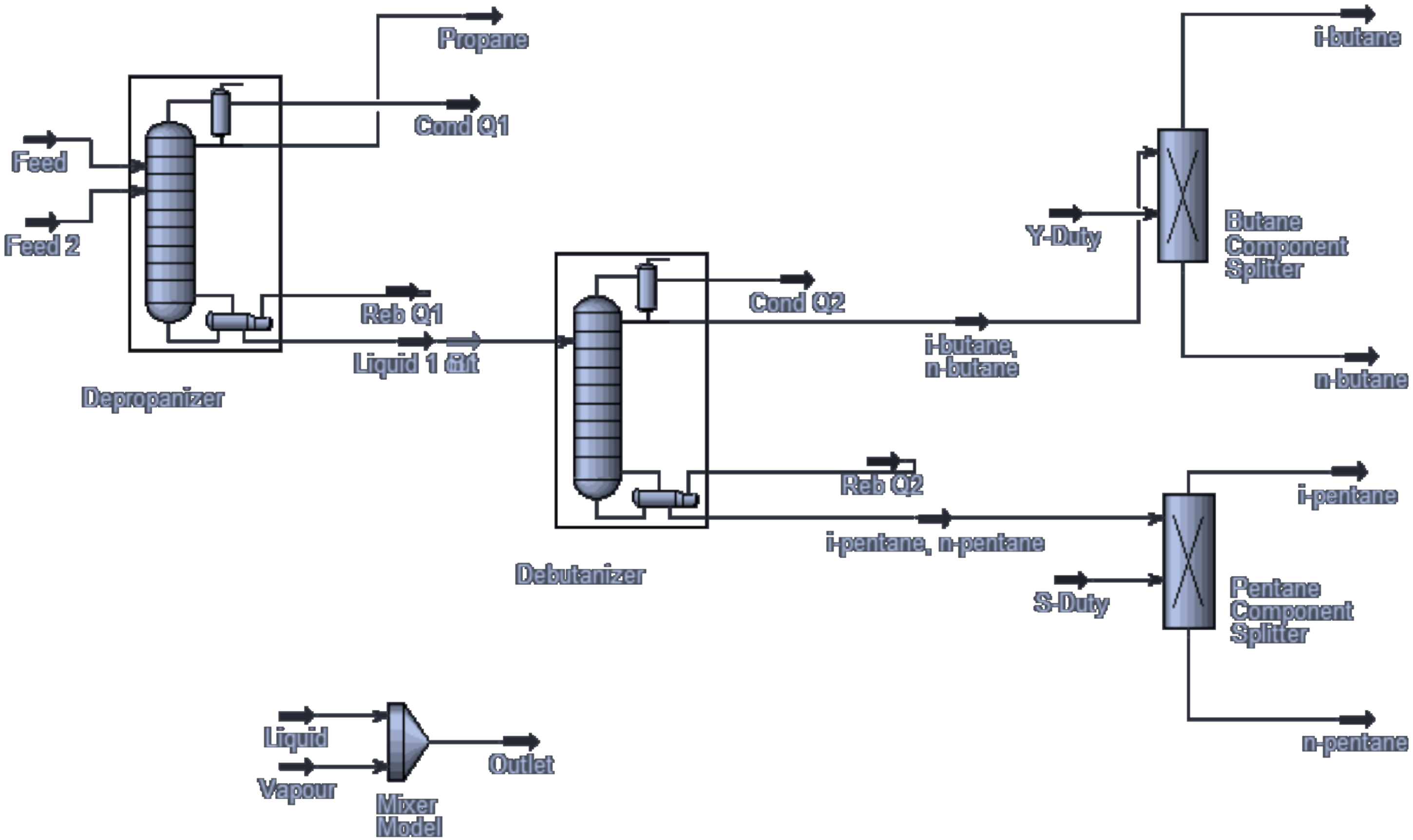


Figure 11. Process flow diagram of the distillation sequence for the converged HYSYS simulation of the multicomponent distillation system

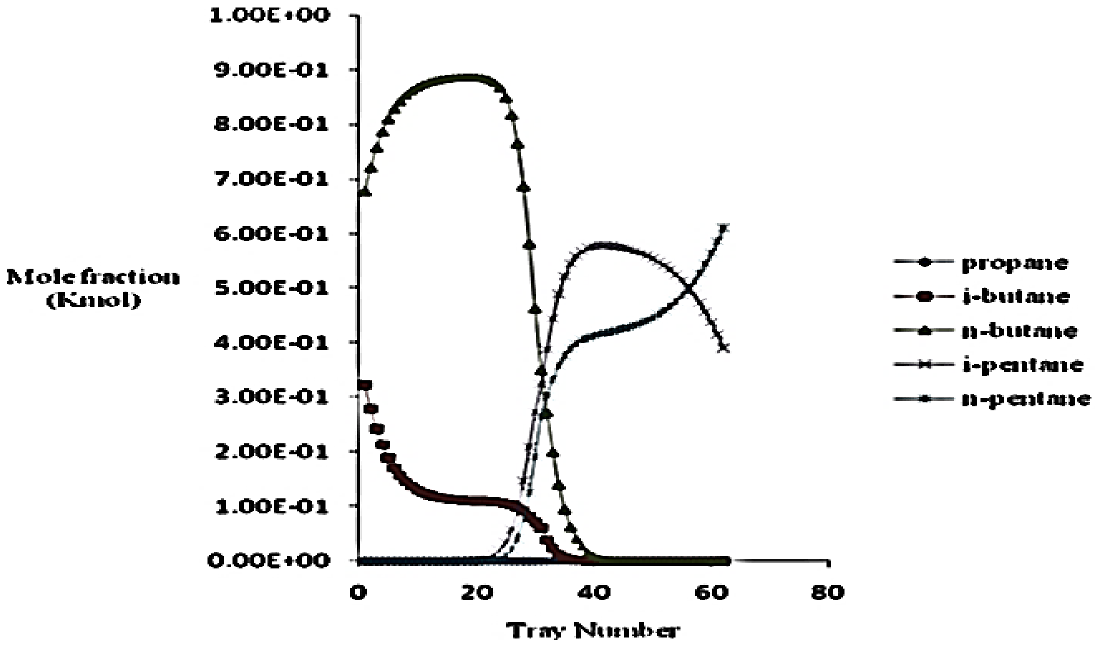


Figure 12. Molar composition profile of the Depropanizer for the converged HYSYS simulation

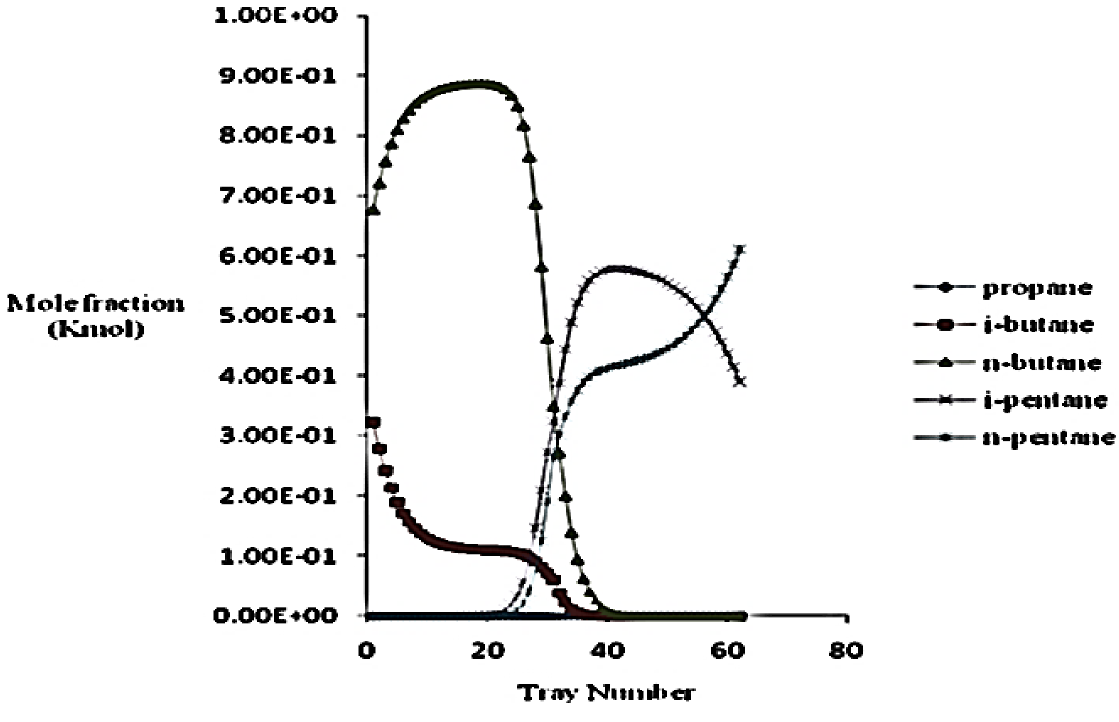


Figure 13. Molar Composition profile of the Debutanizer for the converged HYSYS simulation

Going by the empirical results obtained by exergetic analysis, the profiles are not expected to cross or be constricted; see Figure 14-17 for the sample of crossed profiles for both exergetic efficiency and exergetic destruction profiles. Crossed curves or/and constricted profiles will amount to the somersault of the driving force within the column and system. Such a system is thermo-feasibly infeasible. Constricted cases though thermo-feasible, might be thermo-exegetically efficient but such conditions could render the design inefficient in terms of energy usage thereby leading to high avoidable exergy destruction. The complete profiles of all the 18 systems are included in Appendix B.

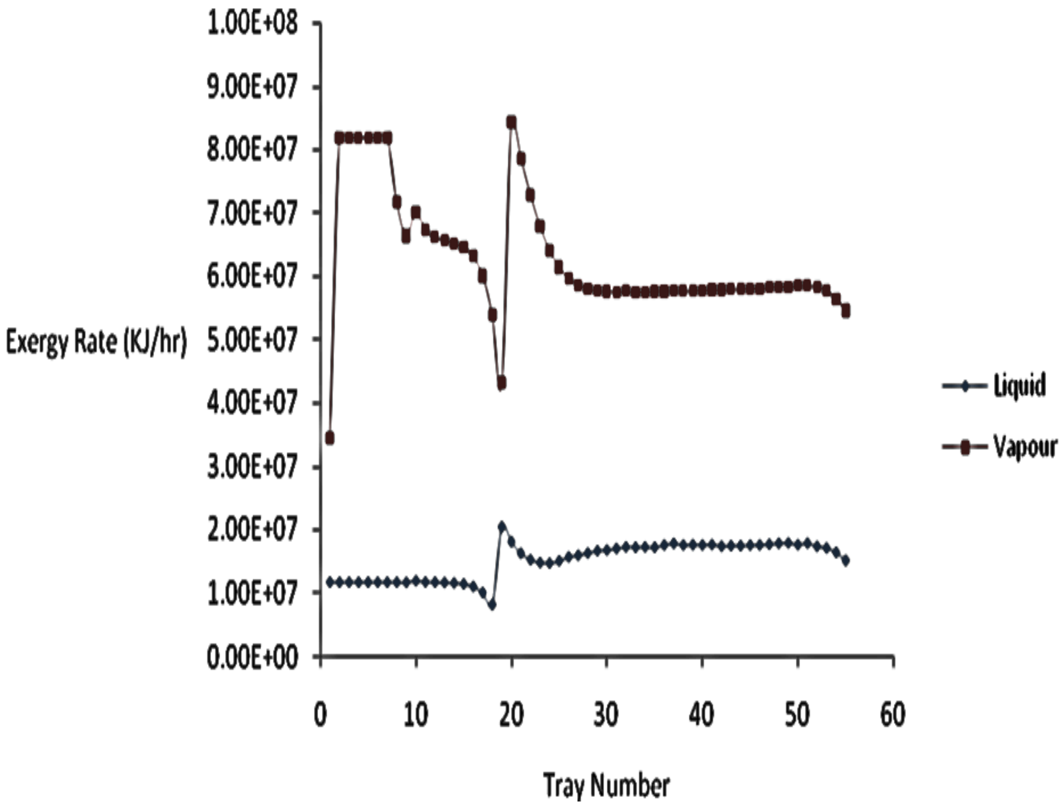


Figure 14. Thermofeasible exergetic profile

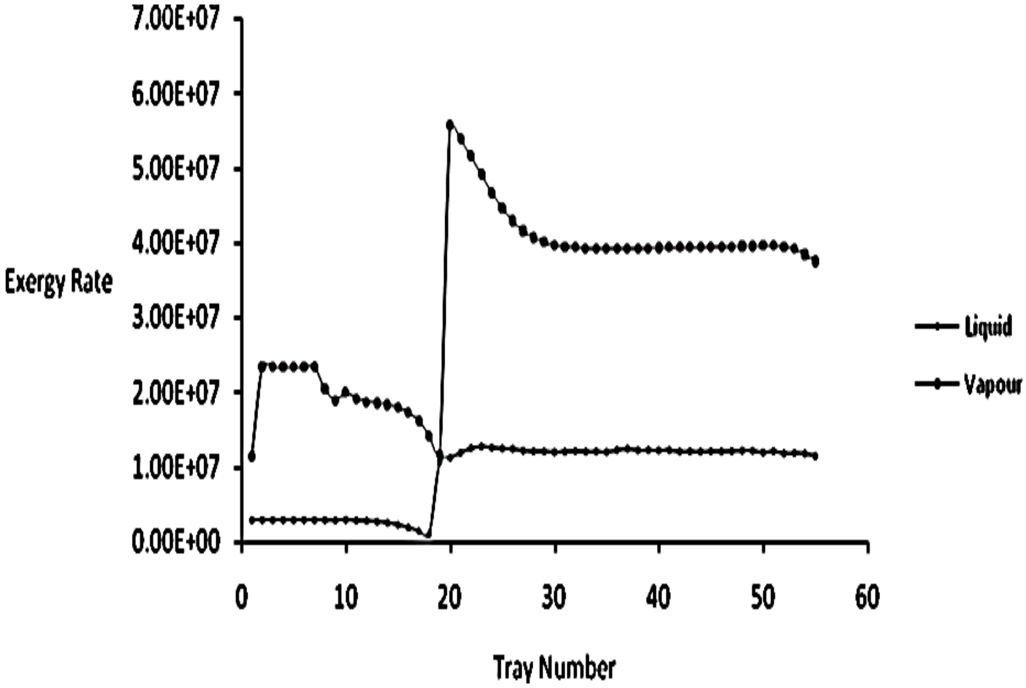


Figure 15. Crossed exergetic profile

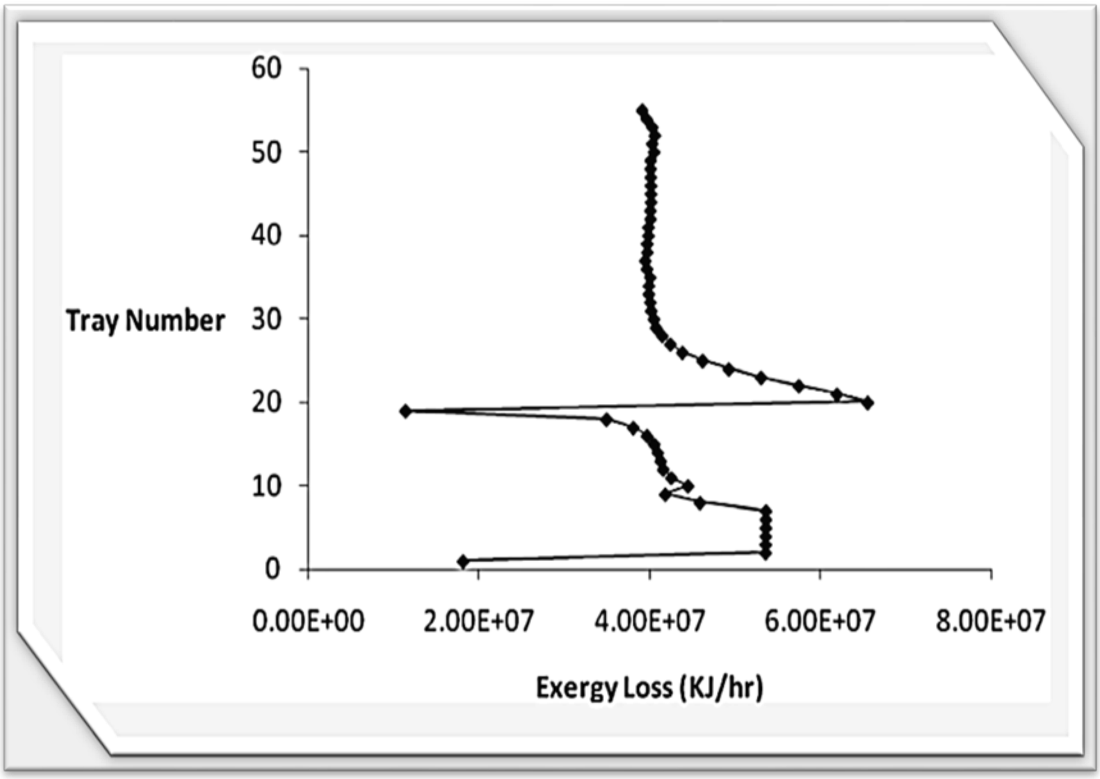


Figure 16. Thermofeasible exergetic destruction profile

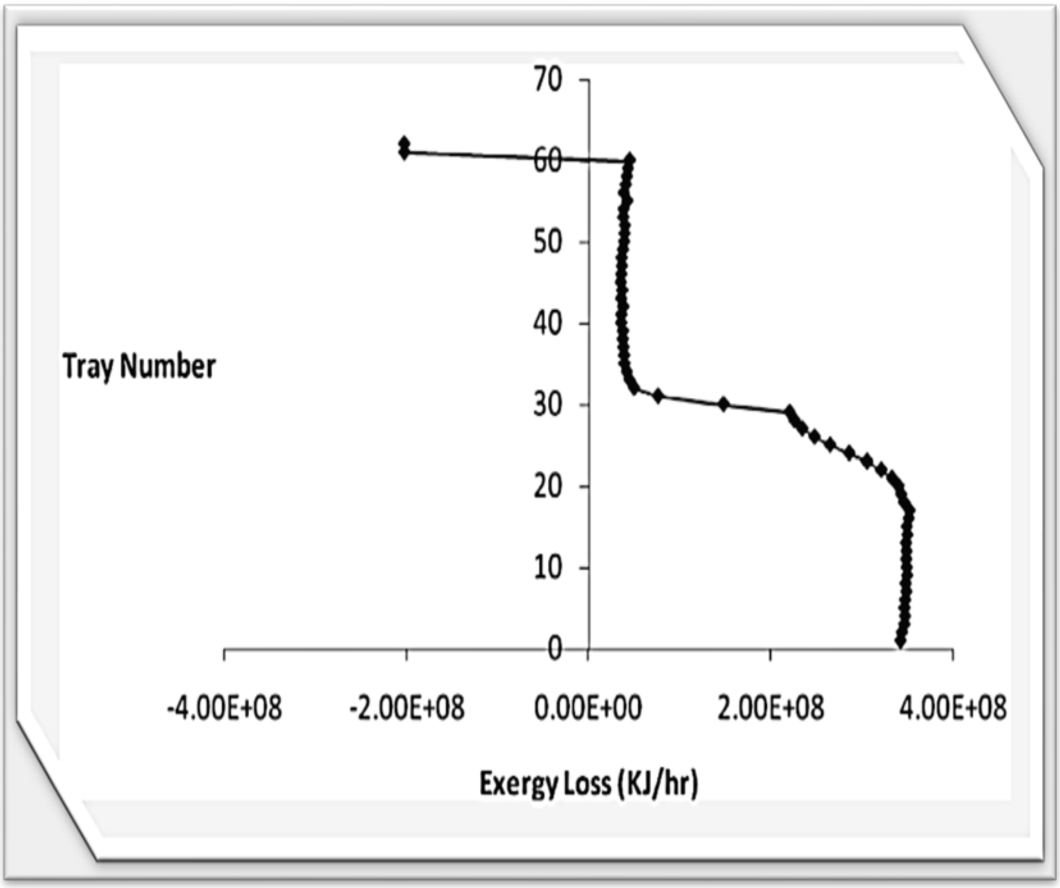


Figure 17. Crossed exergetic destruction

However, the results summarized in Table 19 shows that thermo-exergetic rate profiles of the single base case -30 ^{o}C, -80 ^{o}C, -30 ^{o}C-Reflux ratio 6, -80 ^{o}C-Reflux ratio 6 and base case-Reflux ratio 6 were thermo-feasibly efficient. Profiles of the base case -30 ^{o}C-Reflux ratio 2, -80 ^{o}C. Reflux ratio 2, and base case-Reflux ratio 2 crossed in their depropanizer and thus they are infeasible. Considering thermo-exergetic efficiency, single feed rate base cases with -30 ^{o}C, -80 ^{o}C and reflux ratio 6, gave thermo-exergetic efficiency range of 57.40 – 70% and 65.20% - 54.90% at depropanizer and debutanizer respectively. Multiple feed base cases gave same thermo-exergetic efficiency range of 81.7% and 62.20% at depropanizer and debutanizer respectively compared with that of single feed rate base cases. 800 kPa cases gave 82.1% and 62.5% at depropanizer and debutanizer respectively. 1200 kPa case gave the lowest exergy efficiency at the depropanizer and debutanizer respectively.

From the empirical results of the exergetic destruction, it could be seen that most of exergy destroyed are localised in the stripping section with its constant values starting from tray 30 and remain constant afterwards. This shows that operating this multicomponent distillation system at the feed pressure of 1200 kPa will be unrealistic despite the feasible thermo-exergetic rate and efficiency. Therefore, the situations of the overall column and system have been summarized in Fig 18- 19. Obviously, a uniform distribution of the heat exchanged within the columns results from a uniform distribution of the potential of transfer. These results also complied with previous works of Zemp, *et al.*, 1997 and, Rivero and Koeijer, (2003). Overall exergy destroyed at the debutanizer is greater than at the depropanizer (see Fig 13). Base Cases (-50 ^{o}C-1000KPa-reflux ratio 4), (-30 ^{o}C-1000KPa-reflux ratio 4), and (-30 ^{o}C-1000KPa-reflux ratio 6) seems to be more thermodynamically feasible. From the exergetic analysis of the multicomponent system, rate profiles showed that only 20 systems were thermodynamically feasible. Systems with reflux ratio 2 were thermodynamically infeasible at all conditions except at 193K and 800kPa. The thermo-responses of multiple feeds case 34 gave the same responses with its corresponding base case 7 which imply that both systems will give the same thermo-effect under the same condition with its multiple feed rates and feed stage case. Therefore the multiple feeds case 7 is not included in the DEA and robust parameter design procedure.

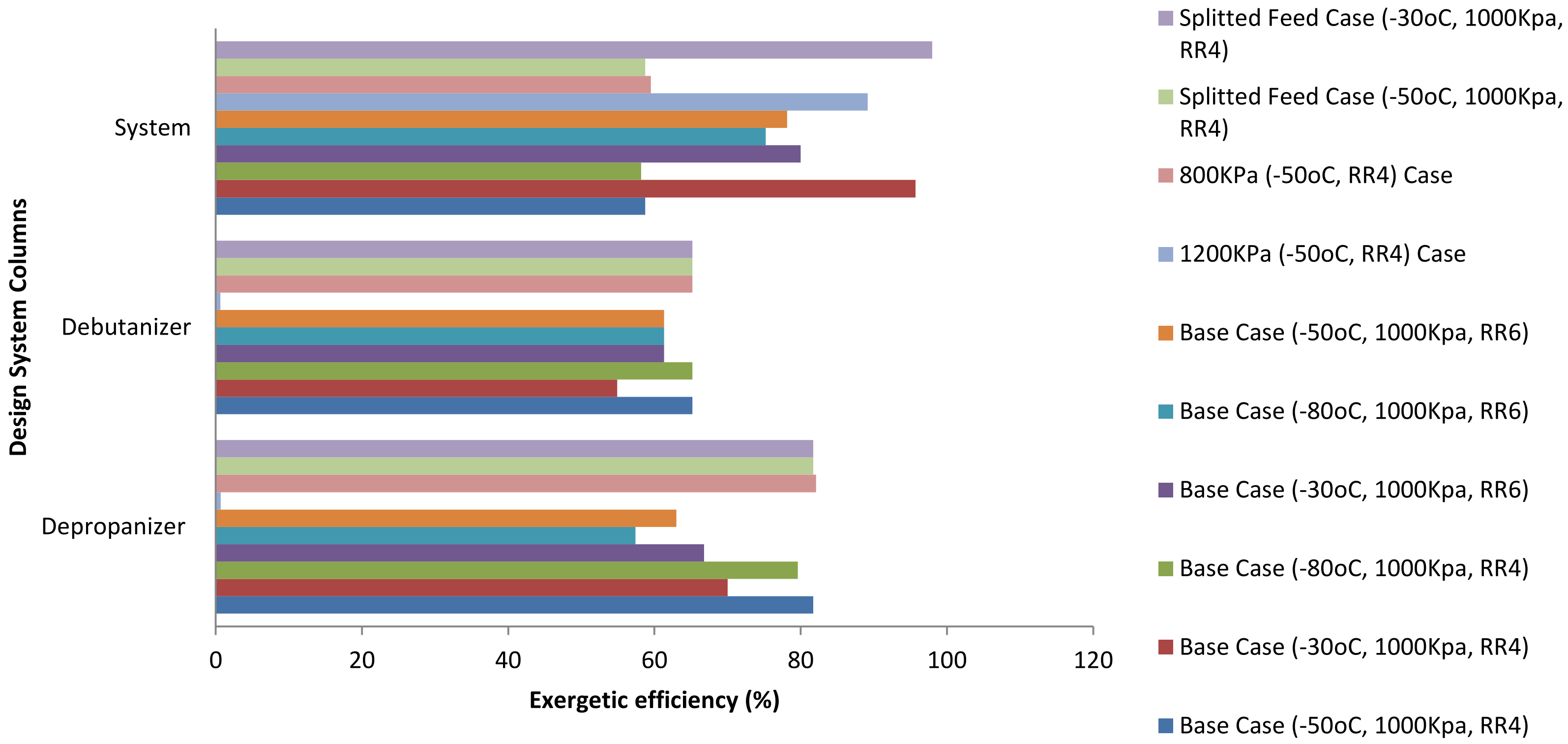


Figure 18. Columns and overall system exergetic efficiency for the thermo-feasible systems

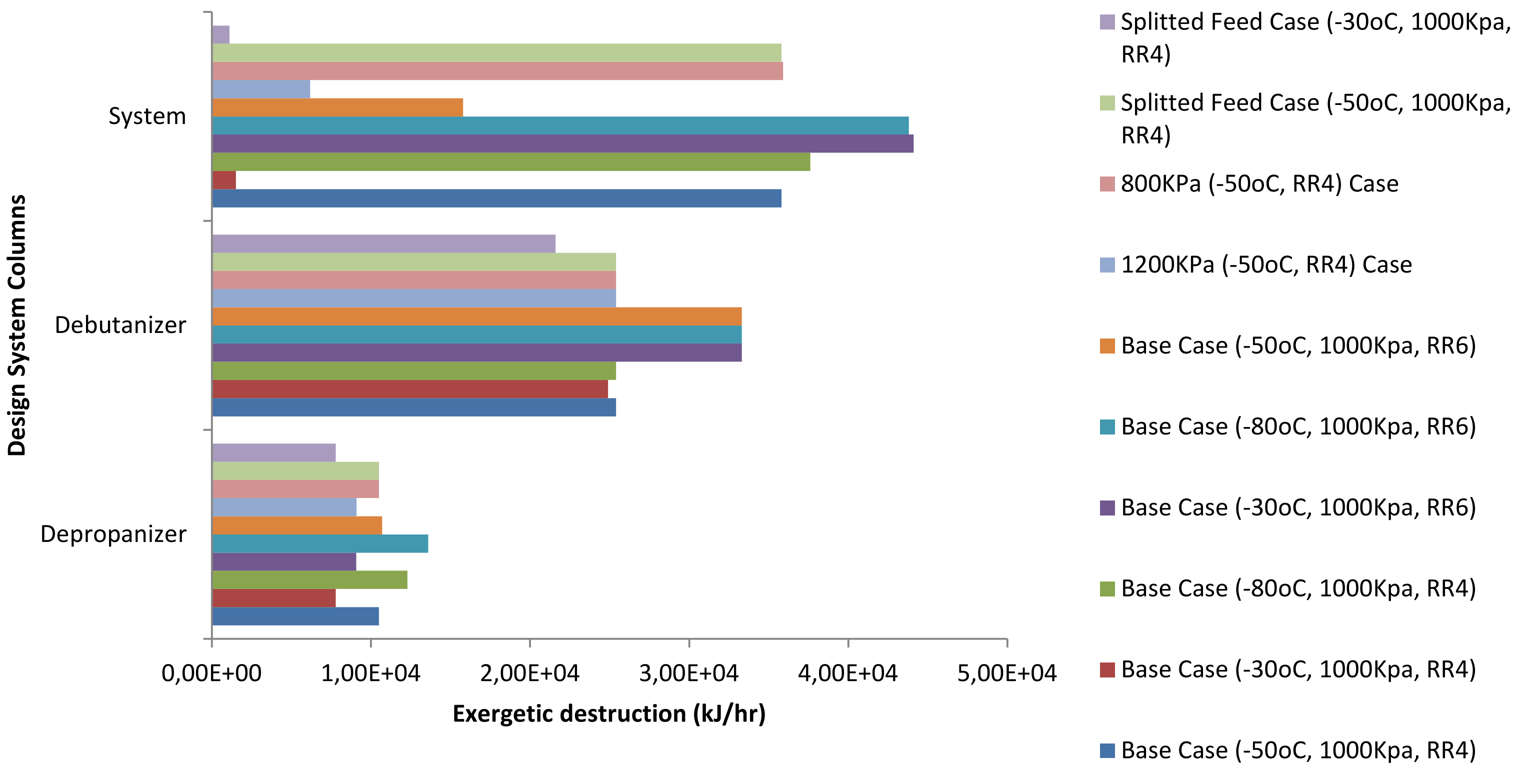


Figure 19. Columns and overall system exergetic destruction rate for the thermo-feasible systems

Table 19. Exergy analysis for thermo-feasible system and their thermo-responses

DMU	Control Factor Combination	Exergy rate profiles		Thermo-feasibility			Thermo-responses	
		Depropanizer	**Debutanizer**	**Depropanizer**	**Debutanizer**	**Whole System**	**Exergetic efficiency (%)**	**Exergtic loss rate (kJ/hr)**
1	223K, 1000kPa, RR4	did not cross	did not cross	feasible	feasible	feasible	58.73	3.58E+7
2	243K, 1000kPa, RR4	did not cross	did not cross	feasible	feasible	feasible	95.70	1.51E+6
3	193K, 1000kPa, RR4	did not cross	did not cross	feasible	feasible	feasible	58.17	3.76E+7
4	243K, 1000kPa, RR2	constricted	did not cross	undesired	feasible	infeasible		
5	243K, 1000kPa, RR6	did not cross	did not cross	feasible	feasible	feasible	79.98	1.41E+7
6	193K, 1000kPa, RR2	crossed	constricted	infeasible	undesired	infeasible		
7	193K, 1000kPa, RR6	did not cross	did not cross	feasible	feasible	feasible	75.22	4.38E+7
8	223K, 1000kPa, RR2	crossed	did not cross	infeasible	feasible	infeasible		
9	223K, 1000kPa, RR6	did not cross	did not cross	feasible	feasible	feasible	78.16	1.58E+7
10	223K, 1200kPa, RR4	did not cross	did not cross	feasible	feasible	feasible	89.18	6.17E+6
11	243K, 1200kPa, RR4	did not cross	did not cross	feasible	feasible	feasible	91.28	4.85E+6
12	193K, 1200kPa, RR4	crossed	did not cross	infeasible	feasible	infeasible		
13	243K, 1200kPa, RR2	constricted	did not cross	undesired	feasible	infeasible		
14	243K, 1200kPa, RR6	did not cross	crossed	feasible	infeasible	infeasible		
15	193K, 1200kPa, RR2	crossed	constricted	infeasible	undesired	infeasible		
16	193K, 1200kPa, RR6	did not cross	did not cross	feasible	feasible	feasible	82.78	1.06E+7
17	223K, 1200kPa, RR2	crossed	constricted	infeasible	undesired	infeasible		
18	223K, 1200kPa, RR4	did not cross	did not cross	feasible	feasible	feasible	93.09	3.79E+6
19	223K, 800kPa, RR4	did not cross	did not cross	feasible	feasible	feasible	59.50	3.59E+7

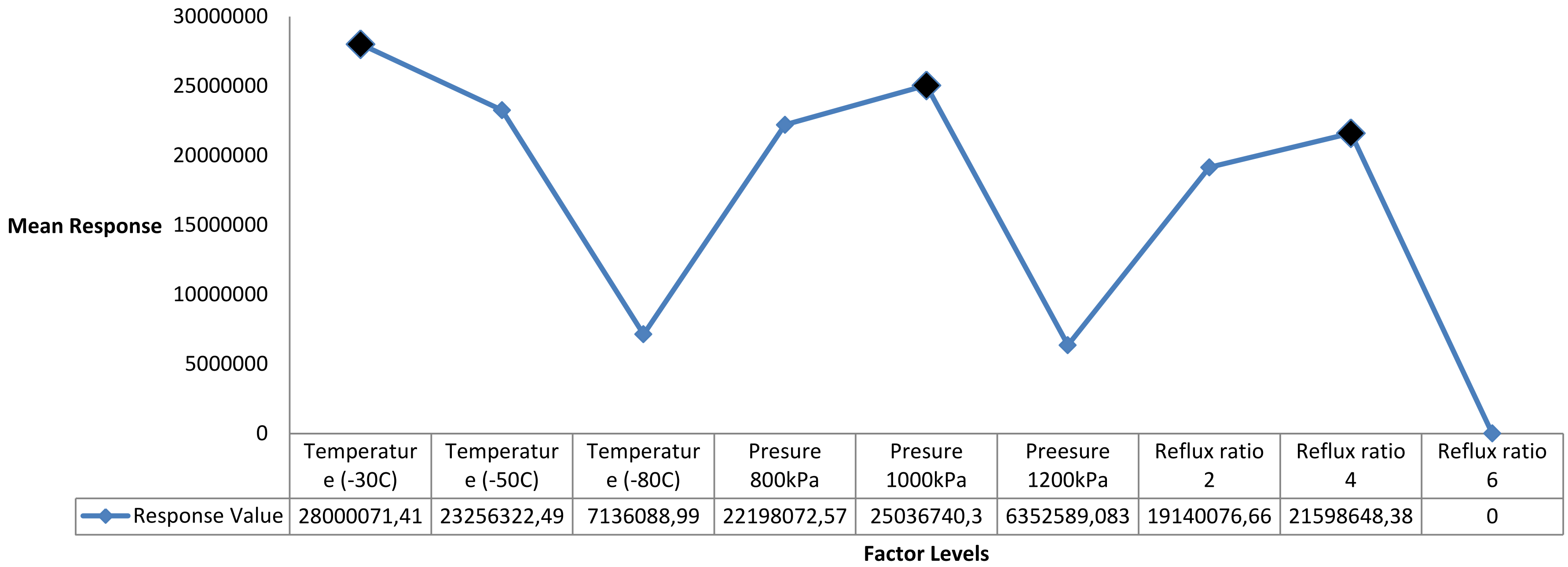
20	243K, 800kPa, RR4	negative profile	did not cross	infeasible	feasible	infeasible		
21	193K, 800kPa, RR4	did not cross	did not cross	feasible	feasible	feasible	58.40	3.74E+7
22	243K, 800kPa, RR2	did not cross	did not cross	feasible	feasible	feasible		-1.19E+7
23	243K, 800kPa, RR6	did not cross	did not cross	feasible	feasible	feasible	80.00	1.41E+7
24	193K, 800kPa, RR2	crossed	did not cross	infeasible	feasible	infeasible		
25	193K, 800kPa, RR6	crossed	constricted	infeasible	undesired	infeasible		
26	223K, 800kPa, RR2	constricted	constricted	undesired	undesired	infeasible		
27	223K, 800kPa, RR6	did not cross	did not cross	feasible	feasible	feasible	86.80	7.79E+6
28	223K, 1000kPa, RR4 Splitted Feed	did not cross	did not cross	feasible	feasible	feasible	58.72	3.58E+7
29	243K, 1000kPa, RR4 Splitted Feed	did not cross	did not cross	feasible	feasible	feasible	97.99	1.12E+6
30	193K, 1000kPa, RR4 Splitted Feed	did not cross	did not cross	feasible	feasible	feasible	82.48	1.06E+7
31	243K, 1000kPa, RR2 Splitted Feed	did not cross	constricted	feasible	undesired	infeasible		
32	243K, 1000kPa, RR6 Splitted Feed	crossed	did not cross	infeasible	feasible	infeasible		
33	193K, 1000kPa, RR2 Splitted Feed	constricted	constricted	undesired	undesired	infeasible		
34	193K, 1000kPa, RR6 Splitted Feed	did not cross	did not cross	feasible	feasible	feasible	75.22	1.86E+7
35	223K, 1000kPa, RR2 Splitted Feed	did not cross	constricted	feasible	undesired	infeasible		
36	223K, 1000kPa, RR6 Splitted Feed	did not cross	did not cross	feasible	feasible	feasible	55.70	4.50E+7

Integrating the empirical results obtained from the exergetic analysis with the partitioning imposed non-parametric revamped VRS model in the robust parameter design, efficient DMUs reduced from 17 to 14 EP and SEP thereby reducing the computational search for the optimum DMU which is within the EPs and/or SEPs.

The discriminatory effect shows that the efficiency of DMUs 1, 2, 28 and 36 changes on partitioning indicating they are either a WEP or those that compared with the WEPs. As given in Table 20, DMUs 1, 2, 5, and 28 turned out to be the weak efficient point (WEP) while DMU 5 is strictly inefficient. This connotes that the inefficient DMUs is not within the convex combinations of the design factors and did not show any possibilities of virtual outputs that can be formed from these design factors. This step is important because it has the tendency of reducing the number of possible frontiers amongst whose optimum sequence can be found. This is another novelty to the method reported by Gutierrez and Lozano (2010). It is uncommon that WEPs will yield optimum output or response of the design factors combination and so they can be dropped from the second DEA (penalization coefficient) estimation. The upper bound variable restriction ε of the VRS model was obtained to be 0.972 and its application revealed that 14 DMUs (3, 7, 9, 10, 11, 16, 18, 19, 21, 23, 27, 29 and 30) are strongly efficient. The optimum DMU can only be found within these 14 DMUs; application of the VRS penalization model shown in Table 20 and by the response graph in Figure 20 revealed that DMU 29 (-30 ^{o}C-1000 kPa-reflux ratio 4) has the highest penalization coefficient of 1 and it is hereby selected as the optimum factor combination to operate the multicomponent distillation system investigated.

Table 20. Efficiency score for standard BCC model, DEA partitioning, facet analysis and optimum factor combination for the Multicomponent distillation case.

DMU	Temperature (C)	Pressure (kPa)	Reflux ratio	Exergy efficiency	Exergy loss rate	Score (θ)	Score (η)	Partitioning	Revamped VRS DEA	Penalization Coefficient
01	2	2	1	0.094	0.945	1	0.991318	WEP	0.503811	
02	3	2	1	0.958	0.081	1	0.998689	WEP	0.9999525	
03	1	2	1	0.077	0.958	1	1	EP, SEP	1	0.966
05	3	2	2	0.640	0.691	0.765	0.941744		0.736529	
07	1	2	2	0.532	1.000	1	1	EP, SEP	1	0.653
09	2	1	2	0.600	0.722	1	1	EP, SEP	1	0.756
10	2	3	1	0.833	0.465	1	1	EP, SEP	1	0.77
11	3	3	1	0.874	0.400	1	1	EP, SEP	1	0.785
16	1	3	2	0.701	0.613	1	1	EP, SEP	1	0.761
18	2	3	1	0.909	0.332	1	1	EP, SEP	1	0.806
19	2	1	1	0.117	0.946	1	1	EP, SEP	1	0.941
21	1	1	1	0.084	0.957	1	1	EP, SEP	1	0.961
23	3	1	2	0.641	0.691	1	1	EP, SEP	1	0.751
27	2	1	2	0.785	0.529	1	1	EP, SEP	1	0.761
28	2	2	1	0.093	0.945	1	0.991214	WEP	0.999744	
29	3	2	1	1.000	0.000	1	1	EP, SEP	1	1
30	1	2	1	0.695	0.613	1	1	EP, SEP	1	0.765
36	2	2	2	0.000	1.007	1	1	EP, SEP	0.526123	



	Temperature (-30C)	Temperature (-50C)	Temperature (-80C)	Presure 800kPa	Presure 1000kPa	Preesure 1200kPa	Reflux ratio 2	Reflux ratio 4	Reflux ratio 6
Response Value	28000071,41	23256322,49	7136088,99	22198072,57	25036740,3	6352589,083	19140076,66	21598648,38	0

Figure 20. Optimal factors setting for integrated data envelopment-thermoexergetic using the proposed model (shaded points)

By implication, exergy analysis would have considered DMUs 2, 5, 7, 9, 10, 11, 16, 18, 23, 27, 29, 30 to be thermo-feasible systems and offered DMUs 1, 3, 19, 21, 28 36 for possible improvement for them to be highly thermo-feasible. Conversely, take, for instance, DMU 2 with the exergetic efficiency of 95.70% and lowest exergetic destruction rate of 1.51E+06 kJ/hr would have been selected as highly efficient system exergetically but it was shown to be inefficient by the integrated model. It means that for DMU 2 to be efficient at the specified operating condition, an improvement is necessary. It is noteworthy that optimum DMU 29 is a multiple feed rate system of DMU 2. This confirms that splitting feed systems (DMUs) and feeding the column at two stages for DMU 2 can serve as an improvement that will make it to be thermo-feasible and efficient.

5.5 Rhamnolipid production

Zulfiqar et al. (2014) presented the fermentation process for the production of rhamnolipid from previous work how to optimize the best consistent conditions for rhamnolipid production by Pseudomonas aeruginosa mutant strain grown on molasses using grey relational analysis in Taguchi design. The main factors incubation time (IT), total sugar (TS) and carbon source (CN). Eight responses; utilized total sugar (UTS), DCBM, ST, and $Y_{x/s}$ are with quality indicator STB while RL, $Y_{p/s}$, $Y_{p/x}$ and P_v are with quality indicator LTB. The table of input and output variables is given in Table 21, signal-to-noise ratio with its corresponding normalized values are in Table 22. The estimation of the upper bound restriction values ofU_o^-, U_o^+ in Table 23 shows for efficient DMUs 1-8 from and ε was obtained to be 0.548. On the application of the proposed model, Table 24 gives at both orientations of DEA, DMU 1-8 are on the frontier and are termed efficient fermentation parameter settings, thereby fall within the region of EP and SEP. On the other hand, DMU 9 is inefficient at both orientations hence it is a WEP. With the modified BCC, DMU 9 is strictly inefficient.

With the proposed method, the efficiency of *DMUs 9* changes indicating that it is either a WEP or its companion and could not have been one of the convex combinations for the possible production set (PPS) of the process. The DEA (Penalization coefficient) estimation yields the highest score of 0.5402 for DMU 7. Therefore by the proposed method, DMU 7 with combination TS_3, CN_{10}, IT_7 is the optimal factor level combination for rhamnolipid production on the orthogonal array (OA). From the response graph, Figure 21, the optimal value of DMU 3 is still on the OA. Generally, a global optimal solution should be on the OA and the response graph in most cases, however, this is not so for this case study. Additionally, the grey relational analysis of Zulfiqar et al. (2014) obtained an optimal setting of TS_2, CN_{20}, IT_3. With this situation, we need to determine the global optimal solution among the two optimal results by performing a confirmatory test. For this, we employ a multivariate multiple dependent general linear model to carry multiple analysis of variance (MMGLM). This is used to evaluate and establish the linear relationship between the multivariate and multiple dependent variables. This multivariate multiple dependent regression is performed in RStudio with the responses captured in a cbind() function at 95% confidence interval as follows;

```
res.man <- manova(cbind(UT,DCBM,RL,ST,Yp/s,Yp/x,Px/s,Pv) ~ TS+CN+IT, data
= my_data)
```

```
mlm1 <- lm(cbind(UT,DCBM,RL,ST,Yps,Ypx,Pxs,Pv) ~ TS+CN+IT, data = my_dat
a)
```

```
mlm1 <- lm(cbind(UT,DCBM,RL,ST,Yps,Ypx,Pxs,Pv) ~ TS+CN+IT, data = my_dat
a)
```

```
lh.out <- linearHypothesis(mlm1, hypothesis.matrix = c("TS = 0", "CN = 0", "IT = 0
"))
```

This led us to the MMGLM model for the response as;

```
Response value <- lm(cbind(UT,DCBM,RL,ST,Yp/s,Yp/x,Px/s,Pv) ~ data =
my_data)
```

Where TS = Total sugars (%), DCBM = Dry cell biomass, CN=Carbon content, IT =Incubation time (days), UT = utilized, RL = Rhamnilipid content produced, Yp/s =substrate biomass, Yp/x = Cell biomass, Px/s = Cell-Substrate biomass, Pv = volume of the biomass yield.

From Table 25, all the independent variables are positively related with RL and DCB M. Negative relationship with the TS; CN and IT are negatively related to Yp/x and Yp/x; IT and TS showing a negative relationship with Yx/s and Yx/s; Pv negatively r elated to IT while UT as expected negatively related to TS.

These trends are in tandem with the finding enumerated by Zulfiqar et al. (2014) abo ut the fermentation dynamics of the process. Next is to verify the relationship of the i ndependent (predictors) variables using MANOVA function in the multivariate test s tatistics as reported by Fox and Weisberg, (2011). For Table 26, the Pillai test and ot her counterpart test statistics of Wilks, Hotelling-Lawley and Roy reveal insignifican t results suggesting that predictors, as analyzed, already included in the model. The MMGLM analysis further shows that the independent variables are necessary for the estimation of the dependent (rhamnolipid content). Table 27 the OA response graph optimal (DMU 3) of the proposed model is a better predictor of the responses with th e highest rhamnolipid content of 1.087 and the total response value of 82.270. Theref ore the optimal value of the response graph OA as DMU 3 TS_1, CN_{30}, IT_7 is selected as the optimum fermentation parameter setting for the production of rhamnolipid.

Table 21. Input and output data Rhamnolipid production case study

	Design Factors Combinations (Input Variables)				Responses (Output Variables)						
DMUs	**TS**	**CN**	**IT**	**UT**	**DCBM**	**RL**	**ST**	**Yp/s**	**Yp/x**	**Px/s**	**Pv**
1	1	10	3	24	0.65	0.8	32	3.33	1.23	2.71	0.0111
2	1	20	5	39	1.11	0.9	31	2.31	0.81	2.85	0.0075
3	1	30	7	47	1.1	0.88	31	1.87	0.8	2.34	0.0052
4	2	10	5	19	1.3	1	30	2.63	0.77	3.42	0.0083
5	2	20	7	26	1.5	1.45	28	2.79	0.97	2.88	0.0086
6	2	30	3	13	1.2	1.2	29	4.62	1	4.61	0.0167
7	3	10	7	19	0.85	0.95	31	1.67	1.12	1.49	0.0056
8	3	20	3	10	1.21	0.9	29.5	3	0.74	4.03	0.0125
9	3	30	5	15	1	1.04	30	2.31	1.04	2.22	0.0087

TS = Total sugars (%), DCBM = Dry cell biomass, CN=Carbon content, IT =Incubation time (days), UT = utilized, RL = Rhamnolipid content produced, Yp/s =substrate biomass, Yp/x = Cell biomass, Px/s = Cell-Substrate biomass, Pv = volume of the biomass yield

Table 22. Signal-to-noise-ratio (SN) and Normalized signal to noise ratio (NSN) for the Rhamnolipid production case

Signal-to-Noise ratio								Normalized Signal-to-Noise ratio							
UT	**DCBM**	**RL**	**ST**	**Yp/s**	**Yp/x**	**Px/s**	**Pv**	**Utout**	**DCBMout**	**Rlout**	**Stout**	**Yp/sout**	**Yp/xout**	**Px/sout**	**Pvout**
-27.60	3.74	-1.94	-30.10	10.45	1.80	-8.66	-39.09	0.57	0.00	0.00	1.00	0.68	0.78	0.53	0.65
-31.82	-0.91	-0.92	-29.83	7.27	-1.83	-9.10	-42.50	0.88	0.64	0.20	0.76	0.32	0.79	0.57	0.31
-33.44	-0.83	-1.11	-29.83	5.44	-1.94	-7.38	-45.68	1.00	0.63	0.16	0.76	0.11	0.82	0.40	0.00
-25.58	-2.28	0.00	-29.54	8.40	-2.27	-10.68	-41.62	0.41	0.83	0.38	0.52	0.45	0.92	0.74	0.40
-28.30	-3.52	3.23	-28.94	8.91	-0.26	-9.19	-41.31	0.62	1.00	1.00	0.00	0.50	0.36	0.58	0.43
-22.28	-1.58	1.58	-29.25	13.29	0.00	-13.27	-35.55	0.17	0.73	0.68	0.26	1.00	0.27	1.00	1.00
-25.58	1.41	-0.45	-29.83	4.45	0.98	-3.46	-45.04	0.41	0.32	0.29	0.76	0.00	0.00	0.00	0.06
-20.00	-1.66	-0.92	-29.40	9.54	-2.62	-12.11	-38.06	0.00	0.74	0.20	0.39	0.58	1.00	0.88	0.75
-23.52	0.00	0.34	-29.54	7.27	0.34	-6.93	-41.21	0.26	0.52	0.44	0.52	0.32	0.18	0.35	0.44

TS = Total sugars (%), DCBM = Dry cell biomass, CN=Carbon content, IT =Incubation time (days), UT = utilized, RL = Rhamnolipid content produced, Yp/s =substrate biomass, Yp/x = Cell biomass, Px/s = Cell-Substrate biomass, Pv = volume of the biomass yield

Table 23. The values of u_o^-, u_o^+ for efficient DMUs for Rhamnolipid production

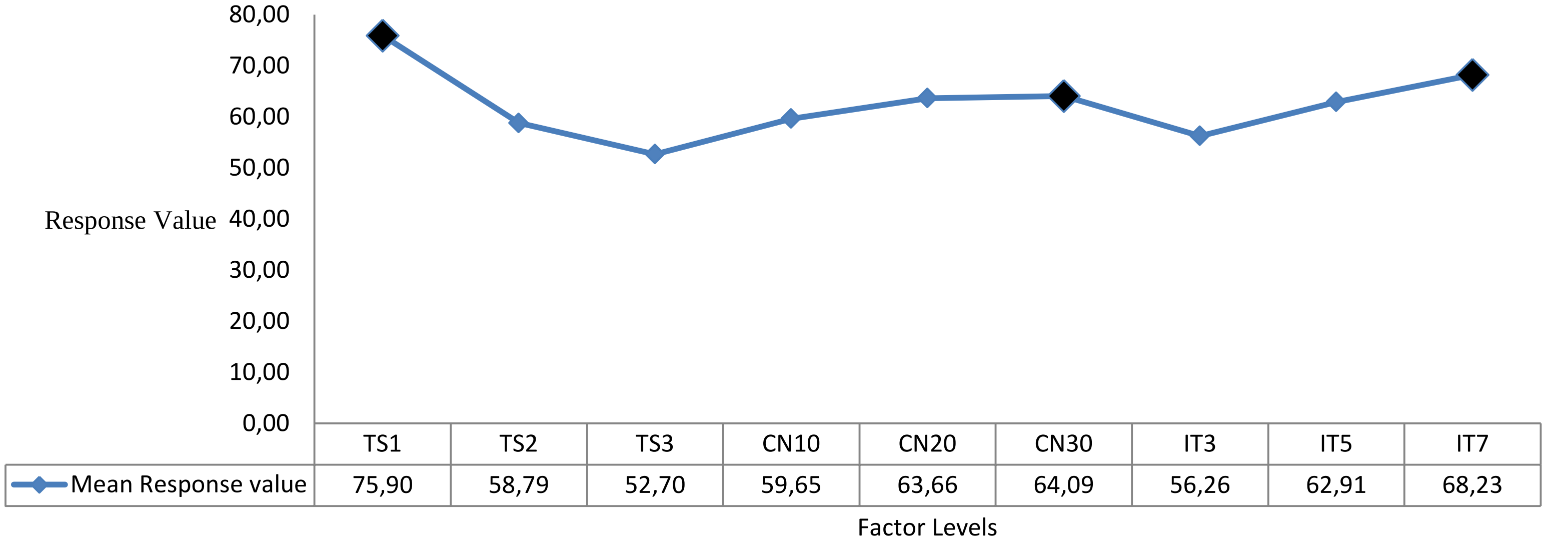
DMUs	u_o^-	u_o^+
1	0.518	1
2	0.397	1
3	0.277	1
4	1	1
5	1	1
6	0.548	1
7	1.200	1
8	1	1

$$\varepsilon = \text{Max } u_o^+/u \neq 1 = 0.548$$

Table 24. Efficiency scores for standard orientations, modified BCC model and penalization coefficient for Rhamnolipid production

DMU	TS	CN	IT	UT	DCBM	RL	ST	$Y_{p/s}$	$Y_{p/x}$	$P_{x/s}$	P_v	Score (θ)	Score (η)	Partitioning	Modified	Penalization
1	1	10	3	0.566	0.000	0.000	1.000	0.678	0.784	0.530	0.650	1	1	EP, SEP	1	0.2376
2	1	20	5	0.879	0.640	0.198	0.762	0.319	0.788	0.574	0.314	1	1	EP, SEP	1	0.2235
3	1	30	7	1.000	0.629	0.160	0.762	0.111	0.822	0.400	0.000	1	1	EP, SEP	1	0.2575
4	2	10	5	0.415	0.829	0.375	0.517	0.446	0.919	0.736	0.401	1	1	EP, SEP	1	0.2156
5	2	20	7	0.617	1.000	1.000	0.000	0.504	0.356	0.583	0.431	1	1	EP, SEP	1	0.2226
6	2	30	3	0.170	0.733	0.682	0.263	1.000	0.274	1.000	1.000	1	1	EP, SEP	1	0.195
7	**3**	**10**	**7**	**0.415**	**0.321**	**0.289**	**0.762**	**0.000**	**0.000**	**0.000**	**0.064**	**1**	**1**	**EP, SEP**	**1**	**0.5402**
8	3	20	3	0.000	0.743	0.198	0.391	0.576	1.000	0.881	0.752	1	1	EP, SEP	1	0.2202
9	3	30	5	0.262	0.515	0.441	0.517	0.319	0.178	0.353	0.441	0.688	0.9629		0.688	

TS = Total sugars (%), DCBM = Dry cell biomass, CN=Carbon content, IT =Incubation time (days), UT = utilized, RL = Rhamnolipid content produced, Yp/s =substrate biomass, Yp/x = Cell biomass, Px/s = Cell-Substrate biomass, Pv = volume of the biomass yield.



TS1-3 = Total sugars (%), DCBM = Dry cell biomass, CN (10, 20, 30) =Carbon content, IT (3, 5, 7) =Incubation time (days), UT = utilized, RL

Figure 21. Response graph showing the optimal Rhamnolipid fermentation process parameter setting using the proposed model (shaded points)

Table 25. Multivariate multiple dependent GLM and MANOVA analysis

```
Response UT :
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  22.4722     7.4810   3.004  0.02996 *
TS          -11.0000     1.9370  -5.679  0.00236 **
CN            0.2167     0.1937   1.119  0.31416
IT            3.7500     0.9685   3.872  0.01174 *

Response DCBM :
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.706389   0.458868   1.539    0.184
TS          0.033333   0.118810   0.281    0.790
CN          0.008333   0.011881   0.701    0.514
IT          0.032500   0.059405   0.547    0.608

Response RL :
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.628333   0.357124   1.759    0.139
TS          0.051667   0.092466   0.559    0.600
CN          0.006167   0.009247   0.667    0.534
IT          0.031667   0.046233   0.685    0.524

Response TS :
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 32.54167    2.04572  15.907 1.79e-05 ***
TS          -0.58333    0.52967  -1.101    0.321
CN          -0.05000    0.05297  -0.944    0.389
IT          -0.04167    0.26484  -0.157    0.881

Response Yps :
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  4.43722    1.09287   4.060  0.00973 **
TS          -0.08833    0.28296  -0.312  0.76751
CN           0.01950    0.02830   0.689  0.52141
IT          -0.38500    0.14148  -2.721  0.04172 *

Response Ypx :
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.048889   0.331957   3.160   0.0251 *
TS           0.010000   0.085950   0.116   0.9119
CN          -0.004667   0.008595  -0.543   0.6105
IT          -0.006667   0.042975  -0.155   0.8828

Response Pxs :
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  4.42000    1.27298   3.472   0.0178 *
TS          -0.02667    0.32960  -0.081   0.9387
CN           0.02583    0.03296   0.784   0.4687
IT          -0.38667    0.16480  -2.346   0.0659 .


Response Pv :
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.520e-02  3.474e-03   4.374  0.00719 **
TS           5.000e-04  8.995e-04   0.556  0.60227
CN           9.333e-05  8.995e-05   1.038  0.34701
IT          -1.742e-03  4.498e-04  -3.872  0.01173 *
```

Table 26. Multivariate Tests

	Df	test stat	approx F	num Df	den Df	Pr(>F)
Pillai	3	1.227891	0.831478	15	18.00000	0.637305
Wilks	3	0.133972	0.817278	15	11.44364	0.649181
Hotelling-Lawley	3	3.848452	0.684169	15	8.00000	0.749470
Roy	3	3.019796	3.623755	5	6.00000	0.074216

Table 27. MMR response prediction output of the optimal model for Rhamnolipid production

Response Prediction model	**Rhamnolipid fermentation parameter setting (Response)**								**Total Anticipated Response**
	UT	**DCBM**	**RL**	**ST**	**Yp/s**	**Yp/x**	**Yx/s**	**Pv**	
DMU 7: (OA optimal)	17.889	1.117	1.067	30.000	1.672	0.986	1.892	0.005	54.628
Gray Relational Analysis	16.056	1.037	0.950	30.250	3.496	0.956	3.723	0.013	56.481
DMU 3: (Response graph optimal)	44.220	1.217	1.087	30.167	2.239	0.872	2.462	0.006	82.270

5.6 Bio fermentation of "Burukutu"

Bio-fermentation experiment for the production of *"Burukutu"* from four design factors and seven product quality responses was conducted. These factors are at two levels each as follows; additive A (level 1- groundmalt, level 2- non groundmalt), B fermentation process (level 1-innoculum, level 2- non-Innoculum), processing method C (level 1- Mashing point, level 2- non-Mashing Point) and preservation techniques D (level 1- preserved pasteurized, level 2-unpreserved pasteurized). The responses which are the sensory and physicochemical qualities of the product with their quality indicator are given as follows; total dissolved solids (TDS), sugar content, alcohol content with STB while colour, taste, flavour and acidity as LTB. Table 28 shows the values of u_o^-, u_o^+ for efficient DMUs 1-6 from and ε was obtained to be 0.0337 from the input and output (Table 29). The signal to noise and its normalized values were presented in Table 30.

Table 28. The values of u_o^-, u_o^+ for efficient DMUs for bio-fermentation of "Burukutu"

DMUs	$\boldsymbol{u_o^-}$	$\boldsymbol{u_o^+}$
1	0	1
2	0	1
3	0	1
4	0	1
5	0	1
6	0.0337	1

$\varepsilon = \mathrm{Max}\, u_o^+/u_o^- \neq 1 = 0.0337$

Table 31 reveals that at both orientations, all the DMUs are on the frontier, efficient and were categorized into EP and SEP. On the application of the proposed method, DMU 1-5 were on the frontier, but the efficiency of DMU 6 changes from 1 to 0.9812 indicating that it is strictly an inefficient DMU and it was discarded. Application of standard BCC model assigned misleading efficiency scores by promoting DMU 6 which ofcourse possesses an unrealistic weighing scheme as an efficient DMU. This case study gives credence to the efficacy of how the proposed modified BCC in robust parameter model can correct the anomalies associated with the classical and standard BCC model. The DEA (Penalization coefficient) estimation yielded the highest score of 0.3565; hence DMU 4 with $A_2B_1C_1D_2$ is optimal on the OA, also the response graph of Figure 22, $A_1B_2C_2D_1$ is obtained. We perform the multivariate multiple dependent general linear model to confirm and select the global optimal solution using the MMGLM R code below. This will establish the linear relationship between the multivariate and the multiple dependent variables. This multivariate multiple dependent regression is performed in R with the responses captured in a cbind() function as follows at 95% confidence interval;

```
res.man <- manova(cbind(Colour,Taste,Flavour,TDS,Sugar, Acidity, Alcohol) ~ A+B+C+D, data = my_data)

mlm1 <- lm(cbind(Colour,Taste,Flavour,TDS,Sugar,Acidity,Alcohol) ~ A+B+C+D, data = my_data)

lh.out <- linearHypothesis(mlm1, hypothesis.matrix = c("A = 0", "B = 0", "C = 0", "D = 0"))

nd <- data.frame(A = 2, B = 1, C = 1, D = 2) –DMU 4 OA optimal

p <- predict(mlm1, nd)

nd <- data.frame(A = 1, B = 2, C = 2, D = 1) – Response graph optimal

p <- predict(mlm1, nd)
```

For Table 32, the Pillai test and other counterpart test statistics of Wilks, Hotelling-Lawley and Roy reveal insignificant results suggesting that predictors, as analysed, already included in the model. The response prediction in Table 33, OA optimal value, DMU 4 ($A_2B_1C_1D_2$) gave the better prediction of the response and it is selected as the global optimal solution from the production of burukutu. From this result, quality "burukutu" can be produced with no addition of ground malt, inoculum fermentation, with adequate mashing process and its shelf-life can be maintained by preserving and pasteurizing.

It is worthy to take note going by the closeness of the penalization coefficient of DMU 3 with DMU 4, 0.3161 and 0.3565 that alternatively and rarely, factors setting of DMU 3, $A_2B_1C_1D_1$ could be used to produce the product. The only difference between the two combinations is in D which is the method of preservation. This preservation technique at times could be swapped without tampering with the sensory and other qualities of the product. However, this submission needed to be substantiated by further studies.

Table 28. Input and output data Bio-fermentation of "Burukutu" production experiment case study

	Design Factors Combinations (Input Variables)				**Responses (Output Variables)**						
DMUs	**A**	**B**	**C**	**D**	**Colour**	**Taste**	**Flavour**	**TDS**	**Sugar**	**Acidity**	**Alcohol**
1	1	1	1	1	4.5	4.5	4.3	7.5	10.5	0.41	2.97
2	1	1	1	2	4.5	4.5	4.3	7.5	10.5	0.38	2.9
3	2	1	1	1	4.5	4.8	4.8	2.8	9.2	0.37	2.01
4	2	1	1	2	4.5	4.5	4.6	2.8	9.2	0.34	2.04
5	2	2	2	1	2.9	2.9	3.2	13.6	10.6	0.57	2.89
6	2	2	2	2	4.4	4.5	4.5	2.9	10.8	0.52	2.83

Table 30. Signal-Noise ratio (SN) and Normalized signal to noise ratio (NSN) for the Bio-fermentation of "burukutu" case

	Signal-to-Noise ratio							Normalized Signal-to-Noise ratio						
DMU	**Colour**	**Taste**	**Flavour**	**TDS**	**Sugar**	**Acidity**	**Alcohol**	**Colour**	**Taste**	**Flavour**	**TDS**	**Sugar**	**Acidity**	**Alcohol**
1	13.06	13.06	12.67	-17.50	-20.42	-7.74	-9.46	1.00	0.87	0.73	0.62	0.82	0.36	1.00
2	13.06	13.06	12.67	-17.50	-20.42	-8.40	-9.25	1.00	0.87	0.73	0.62	0.82	0.22	0.94
3	13.06	13.62	13.62	-8.94	-19.28	-8.64	-6.06	1.00	1.00	1.00	0.00	0.00	0.16	0.00
4	13.06	13.06	13.26	-8.94	-19.28	-9.37	-6.19	1.00	0.87	0.90	0.00	0.00	0.00	0.04
5	9.25	9.25	10.10	-22.67	-20.51	-4.88	-9.22	0.00	0.00	0.00	1.00	0.88	1.00	0.93
6	12.87	13.06	13.06	-9.25	-20.67	-5.68	-9.04	0.95	0.87	0.84	0.02	1.00	0.82	0.88

Table 31. Efficiency scores for standard orientations, modified BCC model and penalization coefficient for bio-fermentation of "burukutu"

DMUs	**A**	**B**	**C**	**D**	**Colour**	**Taste**	**Flavour**	**TDS**	**Sugar**	**Acidity**	**Alcohol**	**Score (θ)**	**Score (η)**	**Partitioning**	**Modified**	**Penalization**
1	1	1	1	1	1.0000	0.8719	0.7287	0.6234	0.8243	0.3623	1.0000	1	1	EP,SEP	1	0.1848
2	1	1	1	2	1.0000	0.8719	0.7287	0.6234	0.8243	0.2153	0.9389	1	1	EP,SEP	1	0.1922
3	2	1	1	1	1.0000	1.0000	1.0000	0.0000	0.0000	0.1637	0.0000	1	1	EP,SEP	1	0.3161
4	2	1	1	2	1.0000	0.8719	0.8950	0.0000	0.0000	0.0000	0.0379	1	1	EP,SEP	1	0.3565
5	2	2	2	1	0.0000	0.0000	0.0000	1.0000	0.8834	1.0000	0.9301	1	1	EP,SEP	1	0.2622
6	2	2	2	2	0.9489	0.8719	0.8408	0.0222	1.0000	0.8223	0.8763	1	1	EP,SEP	0.9812	

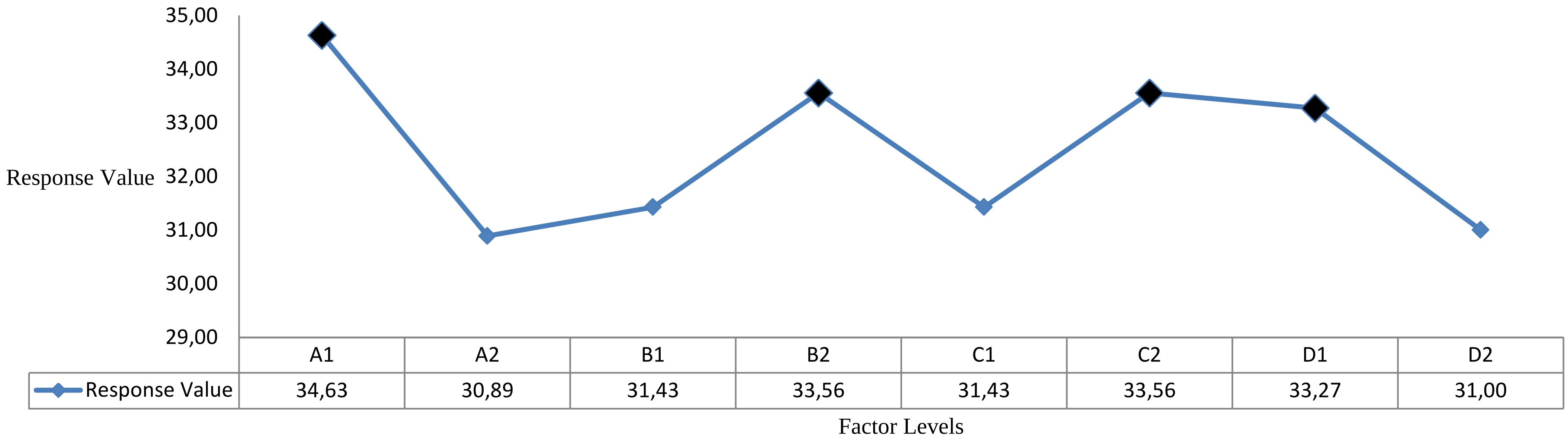


Figure 22. Response graph showing the optimal burukutu fermentation process parameter setting using the proposed model (shaded points)

Table 32. Multivariate Tests

```
                 Df test stat approx F num Df   den Df   Pr(>F)
Pillai            3  1.227891 0.831478     15 18.00000 0.637305
Wilks             3  0.133972 0.817278     15 11.44364 0.649181
Hotelling-Lawley  3  3.848452 0.684169     15  8.00000 0.749470
Roy               3  3.019796 3.623755      5  6.00000 0.074216
```

Table 33. MMR response prediction output of the optimal model for Burukutu fermentation

Response Prediction model	**Burukutu fermentation parameter setting (Response)**							**Total Anticipated Response**
	Colour	**Taster**	**Flavour**	**TDS**	**Sugar**	**Acidity**	**Alcohol**	
DMU 4: (OA optimal)	4.75	4.87	4.88	1.02	9.23	0.34	2.01	27.10
Response graph optimal	3.40	3.33	3.27	14.73	11.97	0.60	3.97	41.09

5.7 Optimum supplier selection framework

Ma *et al.* (2014) proposed an adjustment to the method of Chen (2011) through DEA Game cross efficiency approach where all DMUs are seen as competitors thereby removing the relationship between input and output. The approach considered each DMU as a player in the game with a non-cooperative tendency and through arbitrary plans, assigned efficiency score for desired DMU and set an assumed value for its free variable upon which other DMUs' efficiency was determined.

Unfortunately, none of these previous methods has considered the likely interrelationship between criteria and indicators selected. Furthermore, they all ignored that fact that these criteria and indicators were selected randomly from amongst vast options. Even though their selection was based on the standard concept of SWOT yet the effect of other undetectable indicators on the detectable indicators was not considered. This study views those previous frameworks as a kind of an online quality control based solely and primarily on inspecting suppliers as they are discharged from the SWOT and rejecting those that did fall short of the specified acceptable supplier performance. These previous attempts based their decision on trying to achieve a balance between these desirable but incompatible detectable and undetectable parameters. With the avoidance of doubt, there exist variations between detectable and undetectable parameters. Obviously, those undetected parameters are also influencing the decision making process. It is so obvious that no such appraisal would optimally improve the supplier selection due to variation orchestrated by undetectable factors viewed in this context as undetected supplier performance indicators or simply noise level. Little efforts have been dissipated on how to smoothen the influence of these undetectable parameters. This study seeks to consider the relationship between input criteria and supplier performance through robust signal-to-noise ratio so that supplier performance responses are insensitive to the effects of variations due to the undetected noise indicators.

An optimum framework for supplier appraisal and selection in supply chain co-ordinated decision making that will lead managers, strategic decision makers into optimum appraising, evaluating and selecting the optimum supplier is necessary; therefore a four procedural framework is proposed. In the first procedure, the requirement and strategy analysis where competitive strategies are discerned and all the available supplier selection criteria and performance indicators are evaluated and selected from within all the possible suppliers is carried out using SWOT analysis (Chen, 2011). The view of this procedure is to determine the plausible suppliers. These plausible suppliers are taken further into the second procedure of the robust parameter design where the signal-to-noise ratio is used to render the selection responses insensitive to the effects of the variations due to the undetectable and uncontrollable supplier selection factors. At the third procedure, revamped facet VRS DEA model is employed to determine the weight of each of the performance indicators and evaluate the plausible suppliers in terms of the weighted indicators and the selected criteria. It is possible that sometimes, the optimum supplier could emerge and be selected for this procedure. However, most often probable suppliers are always obtained. In the fourth procedure, the selection responses of the probable supplier obtained by the third procedure are assessed by the VRS penalization coefficient. The view of this is to determine a supplier that will have the highest penalization coefficient. These procedures have been depicted in Fig 23.

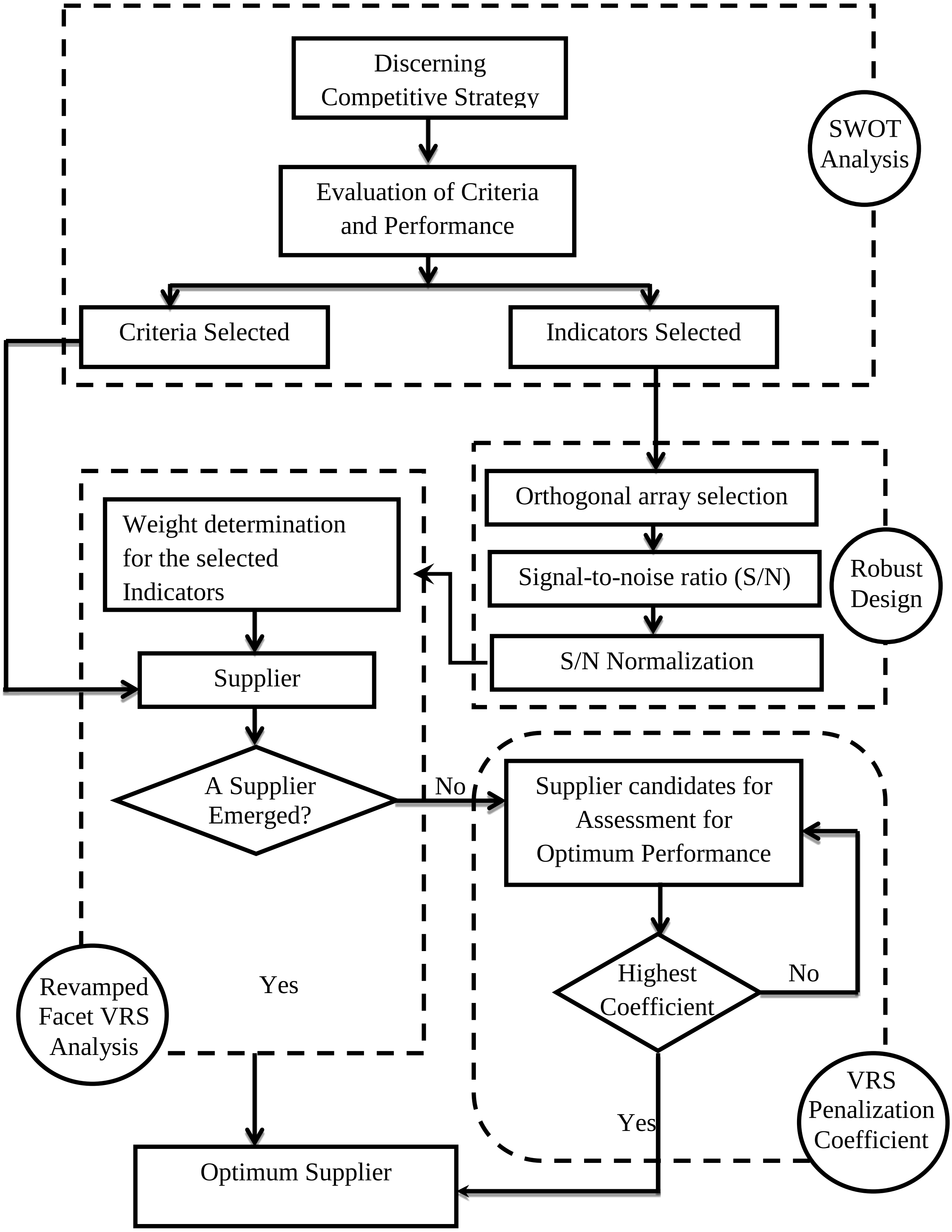


Figure 23. Proposed revamped Facet VRS robust parameter framework for supplier selection optimization

A case study of the Taiwanese textile industry using the performance indicators of 12 textile suppliers obtained from the market observation post system of Taiwan stock exchange, based on the description explained by Chen (2011) shown in Table 34 and which was further analyzed with DEA game cross-efficiency technique of Ma et al. (2014) given in Table 35, is adopted to illustrate the proposed supplier selection framework as shown in Figure 23. We employ five quality responses for the optimal selection of the supplier for the Taiwanian textile. These are R&D rate, productivity, gross profit rate, quality discount (%), and inventory turnover ratio. Three input variables of return rate, discount rate and operating expenses are used. For the robust parameter design, we set the quality attributes of the Larger-The-Better for all the responses. However, since the input variables are assumed to be predictor of the responses, that is, the controllable supplier selection factors, they are used to form the 12 design factor combinations, and each combination is tagged a DMU. These input variables form the inner array of the orthogonal array (OA) for the robust parameter design, so, L_{12} OA is adopted for the robust parameter design phase. Table 36 presents the signal-to-noise ratio (S/N) and are normalized accordingly. The normalized signal-to-noise ratio (NSN) was used in the revamped Facet VRS phase.

Table 37 shows the determination of the restriction for the upper bound variable ε obtained to be 0.9656. As shown in Table 38, at both input and output orientations, *DMUs 2, 4,5,6,7,8,9,10,11 and 12* are all efficient while *DMUs 1 and 3* are inefficient. From the partitioning, suppliers 1 and 3 are WEP while suppliers *2, 4, 5, 6, 7, 8, 9, 10, 11, 12,* are EPs and SEPs. The application of the facet VRS model, DMUs 2, 5, 7, 8 and 10 are on the frontier while DMUs 1, 3, 4, 6, 9, 11 and 12 are inefficient. These analyses put suppliers 1 and 3 as strictly inefficient suppliers and are the worst cases; Supplier 4, 6, 9, 11 and 12 are inefficient and implies that none of these suppliers could be employed. On the other hand, five suppliers 2, 5, 7, 8 and 10 are efficient; this implies that the optimum supplier is within 2, 5, 7, 8 and 10. The penalization coefficient phase gave the highest score of 0.323 for DMU 2; the optimal supplier on the OA based on the framework is Supplier 2. Meanwhile, from the response graph shown in Figure 24, the optimal supplier is DMU 8- another point on the OA. The global optimal solution should be on the OA and the response graph in most cases. Therefore, we need to perform a confirmatory test/response prediction in order to arrive at the global optimal solution. More so, different optimal solutions have been obtained and published by some researchers for the same Taiwanian textile supplier selection problem. The application of the fuzzy base-DEA technique of Chen (2011) also obtained 2, 5, 7, 8 and 10 as the efficient supplier and selected supplier 7 as the optimal.

Similarly, the method of DEA game cross-efficiency of Ma et al. (2014) ranked supplier 10 as the highest supplier but concluded that supplier 12 is the optimum supplier after a game cross efficiency convergence test procedure. The multivariate multiple dependent general linear model is employed as the confirmatory test. MMGLM is adopted to evaluate and establish the linear relationship between more than one independent variable and more than one dependent variable. The independent variables are the multivariate input while the responses are the multiple dependents.

Table 34. Description of performance indicators for Taiwanian firms in selecting a textile supplier

Evaluation criteria	Performance indicators	Description
Quality	Return rate	Return rate = sales return/gross sale; (smaller return rate means sales of better quality products and higher customer acceptance)
	Discount rate	Discount rate = sales discount/gross sales; (smaller discount rate means sales of better quality products and higher customer acceptance)
Cost	Gross profit rate	Gross profit rate = (net sales – cost of goods sold)/sales; (larger supplier gross profit indicates stronger cost control ability)
	Quality discount	Suppliers offer the discount based on purchase quantity; (bigger quantity discount indicate higher cost ability)
Technology and production	R&D rate	R&D rate = R&D expense/sales; (higher supplier R&D rate denotes a stronger technology ability)
	Productivity	Higher supplier productivity means greater supply ability
Organizational management	Inventory turnover ratio	Inventory turnover ratio = cost of goods sold/average inventory; (larger supplier inventory turnover ratio indicates stronger production/marketing control ability)
	Operating expense rate	Operating expense rate = operating expense/net sales; (smaller supplier operating expenses rate expresses higher operating management efficiency)

This multivariate multiple dependent regression is performed in R with the responses captured in a cbind() function as follows at 95% confidence interval;

cbind(R&D rate, Productivity, Gross profit rate, Quantity discount (%), Inventory turnover rate) ~ Return rate + Discount rate + Operating expense rate

mlm1 <- lm(cbind(R&D rate, Productivity, Gross profit rate, Quantity discount (%), Inventory turnover rate) ~ Return rate + Discount rate + Operating expense rate

, data = my_data)

lh.out <- linearHypothesis(mlm1, hypothesis.matrix = c("Return rate = 0", "Discount rate = 0", "Operating expense rate = 0"))

lh.out

Table 35. Parameter for the criteria and performance indicators for the 12 suppliers to a Taiwanian textile industry

Supplier	Input supplier selection criteria			Output supplier performance indicator				
(DMU)	Return rate	Discount rate	Operating expenses rate	R&D rate	Productivity	Gross profit rate	Quantity discount (%)	Inventory turnover ratio
1	0.06	0.66	5.73	1.11	201.00	0.01	7.00	0.67
2	0.54	0.22	2.92	1.13	267.00	9.69	7.00	6.02
3	1.11	0.50	8.38	2.12	311.00	6.36	5.00	5.80
4	0.15	0.48	5.68	1.57	361.00	6.42	5.00	6.17
5	0.19	0.41	4.16	1.50	300.00	9.51	10.00	6.76
6	1.28	0.50	7.01	3.08	310.00	13.81	7.00	7.48
7	0.01	0.01	5.00	2.00	250.00	5.41	8.00	7.04
8	0.42	0.13	2.82	1.04	398.00	6.82	7.00	11.16
9	0.65	1.05	3.83	1.66	375.00	7.51	5.00	5.17
10	0.25	0.07	2.64	2.62	103.00	1.43	8.00	5.16
11	0.72	0.18	4.25	2.09	164.00	6.71	6.00	12.45
12	0.13	1.37	5.55	2.52	200.00	2.98	6.00	6.36

Table 36. The signal-to-noise ratio for the supplier selection for the Taiwanian textile industry

Signal-To-Noise ratio (S/N)				
0.91	26.02	-40.00	16.90	-3.48
1.06	48.53	19.73	16.90	15.59
6.53	49.86	16.07	13.98	15.27
3.92	51.15	16.15	13.98	15.81
3.52	49.54	19.56	20.00	16.60
9.77	49.83	22.80	16.90	17.48
6.02	47.96	14.66	18.06	16.95
0.34	52.00	16.68	16.90	20.95
4.40	51.48	17.51	13.98	14.27
8.37	40.26	3.11	18.06	14.25
6.40	44.30	16.53	15.56	21.90
8.03	46.02	9.48	15.56	16.07

Table 37. The values of u_o^-, u_o^+ for efficient DMUs for the Taiwanian Textile industry

DMUs	u_o^-	u_o^+
1	0.71865	0.71865
2	0.2022	0.2022
3	0.5420	0.5420
4	0.3676	0.3676
5	0.4709	0.4709
6	0.0683	0.0683
7	1.1049	1.1049
8	0.6339	0.6339
9	1.0000	0.9656
10	0.6378	0.6378
11	0.0486	0.0486
12	0.1557	0.1557

$$\varepsilon = \mathrm{Max}\, u_o^+ / u_o^- \neq 1 = 0.9656$$

Therefore, we arrived at the MMGLM model for the response as;

Response value <- lm(cbind(R&D rate, Productivity, Gross profit rate, Quantity discount (%), Inventory turnover rate) ~ Return rate + Discount rate + Operating expense rate, data = my_data).

However, the + signs do not necessarily translate to adding-up but it rather means to model the dependents (responses) as a function of the independent (input variables). Table 39 shows that all the independent variables are positively related with R&D

rate; productivity reveals a negative relationship with the operating expense rate; discount rate and operating expense rate are also negatively related to gross profit rate and inventory turnover rate; the quantity discount (%) show a negative relationship with all the independent variables. We need to check how the independent (predictors) variable affect the model, the use of multivariate test statistics including MANOVA function is used as described by Fox and Weisberg, (2011). The MANOVA analysis, Pillai test statistic reveals insignificant results that suggest that predictors, as tested, are already in the mode. Further multivariate test in Table 40 confirmed through other similar test statistics of Wilks, Hotelling-Lawley and Roy gave the same results with Pillai test and could be interpreted in the same manner. Affirmatively from MMGLM analysis, independent variables could be necessary for the estimation of the dependent (supplier selection performance indicators). For the prediction, the input values of the OA optimal DMU 2, response value graph DMU 8, fuzzy based-DEA model (Chen, 2011), DMU 7 DEA game cross-efficiency model (Ma et al., 2014) DMU 10 and that of convergence procedure of game cross-efficiency (Ma et al., 2014) DMU 12 in Table 38 are used to predict the value of the responses. The total anticipated response from a model is the sum of the predicted responses for that particular model.

As given in Table 41 the OA optimal of the proposed model is a better predictor of the responses except for the R&D rate which DEA game cross efficiency model gave a higher value than that of the OA. Similarly for the total anticipated response, OA optimal of the proposed model gave the highest predicted value of 303.8877, followed by response value also of the proposed model. Therefore the optimal value of the OA of the proposed model obtained as DMU 2 (supplier 2) is selected as the global optimal solution for the supplier selection problem of the Taiwanian textile industry under the condition of the given input and output factors. Although our proposed model is not a raking method per se, however, base of the results obtained, we can categorize the efficient suppliers according to their performance as;

$$\text{Supplier } 2_{\text{DMU } 2} > \text{Supplier } 8_{\text{DMU } 8} > \text{Supplier } 10_{\text{DMU } 10} > \text{Supplier } 12_{\text{DMU } 12} > \text{Supplier } 7_{\text{DMU } 7}$$

It is worthy to note that MMGLM is necessary only whenever the optimal value obta ined for OA and the average response value graph is not the same.

Table 38. Efficiency scores for standard orientations, modified BCC model and penalization coefficient for the supplier selection of Taiwanian textile industry

DMU	Input variables			Response					Score (θ)	Score (η)	Revamped Facet VRS	Penalization coefficient
	Return rate	Discount rate	Operating expenses rate	R&D rate	Productivity	Gross profit rate	Quantity discount (%)	Inventory turnover ratio				
1	0.06	0.66	5.73	0.06	0.00	0.00	0.49	0.00	0.81	0.63	0.81	Inefficient
2	0.54	0.22	2.92	0.08	0.87	0.95	0.49	0.72	1.00	1.00	1.00	0.32
3	1.11	0.50	8.38	0.66	0.92	0.89	0.00	0.70	0.65	0.97	0.41	Inefficient
4	0.15	0.48	5.68	0.38	0.97	0.89	0.00	0.72	1.00	1.00	0.84	Inefficient
5	0.19	0.41	4.16	0.34	0.91	0.95	1.00	0.76	1.00	1.00	1.00	0.25
6	1.28	0.50	7.01	1.00	0.92	1.00	0.49	0.80	1.00	1.00	0.55	Inefficient
7	0.01	0.01	5.00	0.60	0.84	0.87	0.68	0.78	1.00	1.00	1.00	0.27
8	0.42	0.13	2.82	0.00	1.00	0.90	0.49	0.96	1.00	1.00	1.00	0.30
9	0.65	1.05	3.83	0.43	0.98	0.92	0.00	0.66	1.00	1.00	0.87	Inefficient
10	0.25	0.07	2.64	0.85	0.55	0.69	0.68	0.65	1.00	1.00	1.00	0.29
11	0.72	0.18	4.25	0.64	0.70	0.90	0.26	1.00	1.00	1.00	0.82	Inefficient
12	0.13	1.37	5.55	0.82	0.77	0.79	0.26	0.74	1.00	1.00	0.88	Inefficient

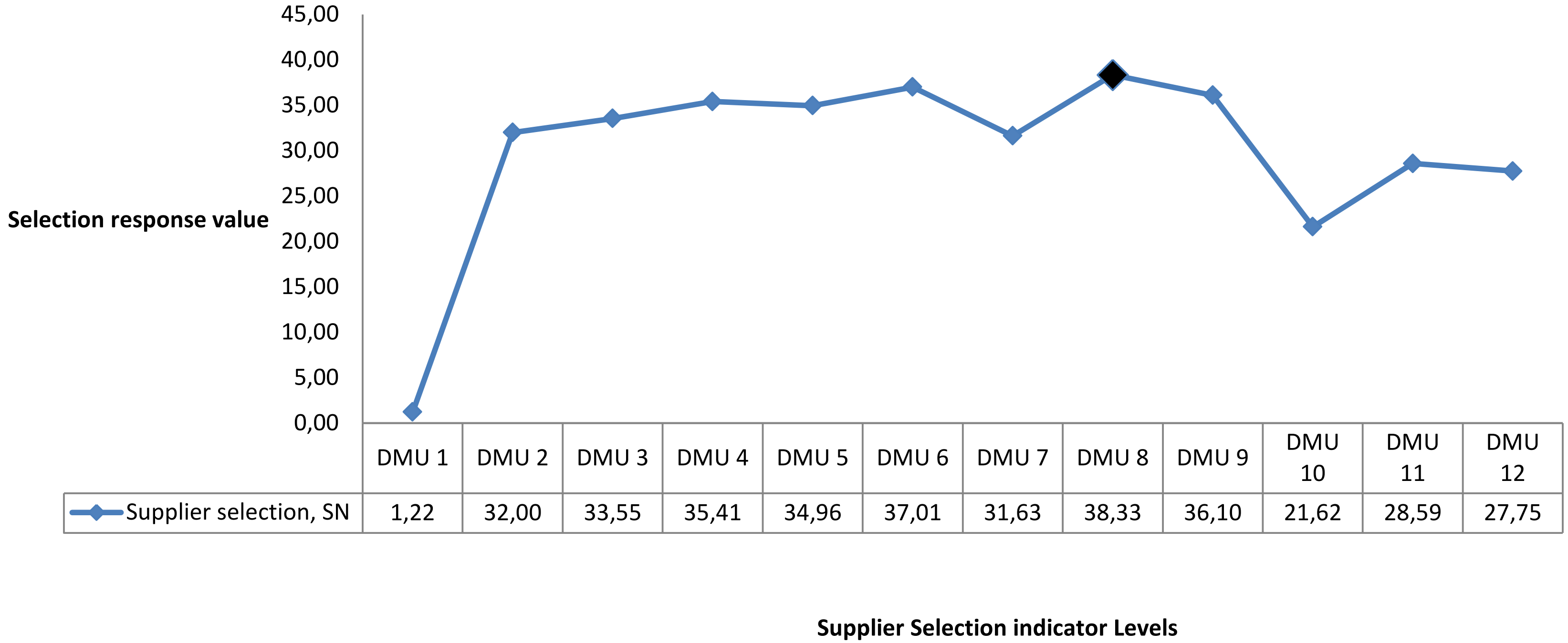


Figure 24. Response graph showing the optimal Supplier selection factors setting using the proposed model (shaded points)

Table 39. Multivariate multiple dependent GLM and MANOVA analysis

```
Response R&D rate
Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.17774    0.59350   1.984   0.0825
a            0.48598    0.54630   0.890   0.3996
b            0.10970    0.53406   0.205   0.8424
c            0.08655    0.13709   0.631   0.5454

Response Productivity
Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept)   243.91     110.32   2.211    0.058
a             112.75     101.55   1.110    0.299
b              23.17      99.27   0.233    0.821
c             -10.67      25.48  -0.419    0.686

Response Gross profit rate
Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept)   5.4737     2.9056   1.884   0.0963
a             6.3950     2.6745   2.391   0.0438 *
b            -0.7417     2.6146  -0.284   0.7839
c            -0.3471     0.6711  -0.517   0.6190

Response Quantity discount (%)
Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept)   8.4294     1.2568   6.707 0.000152 ***
a            -1.1166     1.1569  -0.965 0.362742
b            -1.4476     1.1310  -1.280 0.236432
c            -0.1022     0.2903  -0.352 0.733972

Response inventory turnover ratio
Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept)   8.8911     2.5232   3.524   0.0078 **
a             2.9754     2.3226   1.281   0.2360
b            -1.8825     2.2705  -0.829   0.4311
c            -0.5528     0.5828  -0.948   0.3707
```

Type II MANOVA Tests: Pillai test statistic

```
  Df test stat approx F num Df den Df Pr(>F)
a  1   0.67143  1.63480      5      4 0.3272
b  1   0.33419  0.40155      5      4 0.8280
c  1   0.20704  0.20888      5      4 0.9418
```

Footnote: a = return rate, b = discount rate and c = operating expense rate

Table 40. Multivariate Test

	Df	test stat	approx F	num Df	den Df	Pr(>F)
Pillai	3	1.227891	0.831478	15	18.00000	0.637305
Wilks	3	0.133972	0.817278	15	11.44364	0.649181
Hotelling-Lawley	3	3.848452	0.684169	15	8.00000	0.749470
Roy	3	3.019796	3.623755	5	6.00000	0.074216

Table 41. MMR response prediction output of the optimal model

	Supplier selection performance indicators (Response)					
Response Prediction model	**R&D rate**	**Productivity**	**Gross profit rate**	**Quantity discount (%)**	**Inventory turnover ratio**	**Total Anticipated Response**
DMU 2: (OA optimal)	1.7170	278.7411	7.7503	7.2096	8.4696	303.8877
DMU 7: (Fuzzy base DEA model)	1.1164	191.9265	3.7946	7.8929	6.1383	210.8687
DMU 8: (Response graph optimal)	1.6402	264.1927	7.0843	7.4841	8.3373	288.7386
DMU 10: Cross efficiency optimal	1.5354	245.5554	6.1042	7.7792	8.0439	269.0181
DMU 12: Convergence procedure of DEA game cross efficiency)	1.8716	231.0971	3.3625	5.7340	3.6311	245.6962

Chapter 6

CONCLUSION AND RECOMMENDATION

6.1 Conclusions

This study proposes a modified VRS- robust optimization framework for optimizing multi-quality response system. Efficiency determination and optimization to select the optimum parameter settings were achieved in the most simplified, adequate and effective manner going by the results of its illustration with three real case studies; it provided the largest anticipated improvement in the cases illustrated against all other previously used approaches of PCA, DEAR, GA and benevolent formulation (cross-evaluation technique). Furthermore, this proposed method enhanced other multi-response methods through the following advantages:

- The suggestion of using the fractional factorial number of the orthogonal array achieved in the robust design as the number of neurons in the hidden layer of BPNN proved adequate and capable of reducing errors and uncertainties over the use of contemporary searches.
- Estimation of the restriction for the upper bound of the free variable of the VRS determined by self-evaluation within the DMUs removes errors due to improper setting of the non-Archimedean infinitesimal as proposed by some previous works.
- The partitioning and the modification provide an adequate selection of the optimum parameter settings through its enhanced discriminatory tendency of efficient DMUs.

- In addition to the aforementioned, the approach neither requires any initial information nor assumptions or pre-settings about the output (response) weights thus; the proposed framework is not based on any cogent assumptions like PCA, GA and other previous approaches.

In overall, the proposed approach computed the adequate (pure) frontier/efficiency of the DMUs as many inefficient DMUs that would have been promoted as efficient by the standard DEA models were revealed. More interestingly is the discriminative tendency that further gives insight to DMUs that are within the convex set of the factor level settings and those that should not be considered within the search thereby making the computation search easy and simple compared to other reported methods. These attributes could fascinate quality/process/product engineers, project managers, operational managers, and even top managers that are involved in decision making to espouse these proposed procedures in an extensive range and scope of design, manufacturing and production applications for optimizing multi-quality response processes in the robust parameter design strategy.

Similarly, the proposed integrated data envelopment analysis and robust parameter design procedures can interrelate effectively and efficiently with exergetic analysis especially those involving multiexergetic response. The framework gives vivid panoramic insight into those systems that actually need improvement. Furthermore, the imposed partitioning helped to increase the discrimination among the efficient DMUs, reduction in the number of possible frontiers was achieved, and computational search for the optimum (OFLC) DMU was thereby simplified. The followings can be emphasised about the outcome of this study;

- Supporting thermo-exergetic evaluation with the DEA will reduce complexities in terms of computations and number assumptions required by the engineer to arriving at the optimum operating parameter level setting for multicomponent distillation system.
- Integrating DEA into thermodynamic analysis has the ability to simplify the whole process hereby making it simple, easy to understand and apply by any practitioner.
- The approach is more advantageous and could be implemented over a wide range, to solve thermo-exegetic problems with multi-response problems in manufacturing for strategic decision making by engineers, operators or managerial level.
- These attributes could fascinate quality/process/product engineers, project managers, operational managers to imbibe the proposed procedures in an extensive range and scope for optimizing energy-intensive systems especially those with multi-response processes in the robust parameter design strategy.

We proposed a facet VRS signal-to-noise robust parameter framework for the optimum supplier selection. SWOT is first carried out to determine and select various supplier selection criteria that will be used to appraise suppliers' performance. Robust signal-to-noise parameter design is applied to smooth the effects of variations of the anticipated supplier selection performance responses. By utilizing a partitioning imposed modified VRS model, a revamped facet VRS procedure is engaged to estimate the weights of the input and output selection factors and VRS penalization is used to determine the optimal on the orthogonal array (OA) of the robust procedure. The optimal solution obtained from the response graph of the robust parameter design was different from that of the OA, hence a confirmatory test of multivariate multiple dependent general linear model (MMGLM) is used to check for the independent that is germane for the prediction of the response and to determine the global optimal solution between OA and response graph optimal values. The followings can be concluded about the study:

- Adequate selection of the optimum supplier selection indicators setting is achieved, through the enhanced discriminatory tendency within and between the efficient suppliers as a result of the imposed partitioning.
- The proposed model self-evaluate within its procedure to estimate the input and output weights; therefore, there is no need for prior information and or assumptions like fuzzy base DEA, DEA game cross efficiency and other DEA based methodologies.
- Multivariate multiple dependent regression model (MMGLM) could be used to determine the independent factors that are important to the estimation of the response and to decipher between OA optimal and response value graph optimal to arrive at the global optimal suppliers.
- The framework is simple to implement and could be implemented over a wide range, to supplier selection problems in supply chain management for strategic decision at all levels.

Generally, the proposed supplier selection approach could identify within its procedures those inefficient suppliers that would have been promoted as efficient by the standard DEA models as used in the Fuzzy based DEA and DEA game models. Hence it will then become easier and much more simplified to select the optimal supplier that can be adequate enough to deliver the anticipated output in the presence of other unforeseen supplier factors (uncontrollable noise factors). With these advantages; simplicity, discriminatory tendency, specificity and unambiguity features, top logistic managers, operational managers, supply chain stakeholders, contracting and consulting firms and other decision makers would find this framework appropriated and useful.

6.2 Recommendations

However, more studies on the application of the suggested fractional factorial number of the orthogonal array as the number of neurons in the hidden layer of BPNN and its consistency in predicting the values of the responses beyond the experimented input variables are necessary in order to generalize the viability of the BPNN in the proposed model. The author would also like to extend its application comparatively, to other approaches such as DEA competitive games, Virtual DEA and fuzzy multi-response which have not been fully integrated into the robust parameter strategy.

In view of the integrated exergetic analysis with the proposed model, it should be bored in mind that majorly PR EOS is applicable to an ideal and non-ideal hydrocarbon system due to the enhancement of PR model in HYSYS. However, whenever a highly non-ideal system is encountered another model especially the Activity Models is recommended. Another way to go is to select all the property package filters during the simulation. This could help to deal with any occurrence of non-ideality within the system. Moreover, there is the need to carry out the sensitivity analysis of the thermo-feasible system with the proposed approach. The effect of the cost elements such as total cost and total profit and a capacity factor since most managers are most likely to critically consider the financial and capacity factor of the would-be optimum process. It is also important to see how competitive DEA games will shift the results of the proposed framework.

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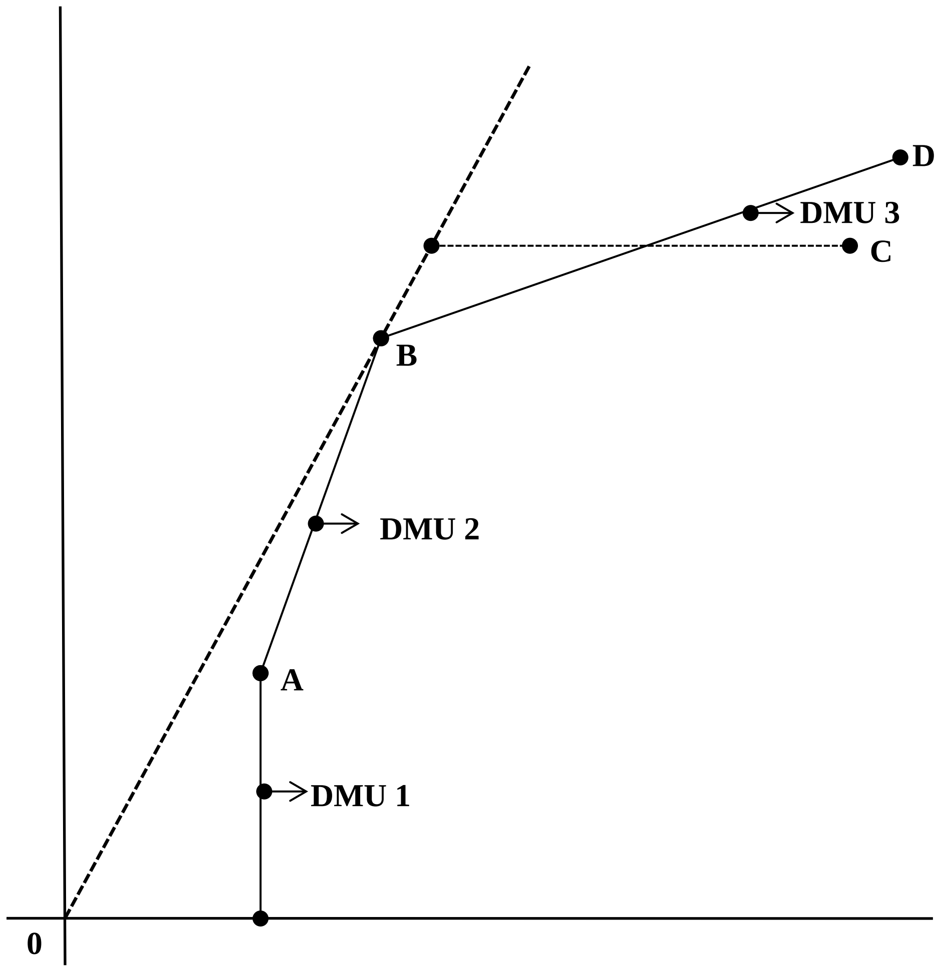
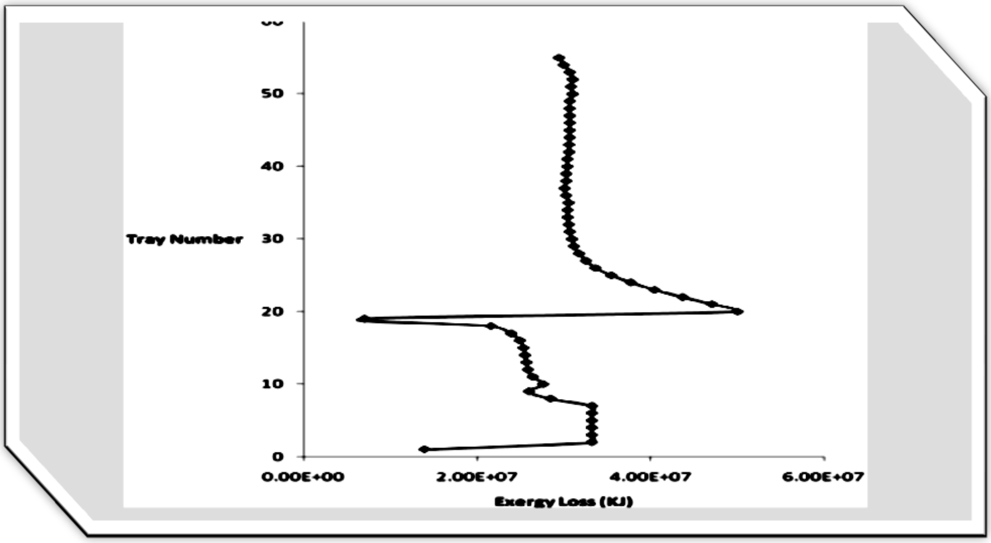
APPENDICES

Appendix A: Graphical explanation of DMUs as WEP, EP and SEP

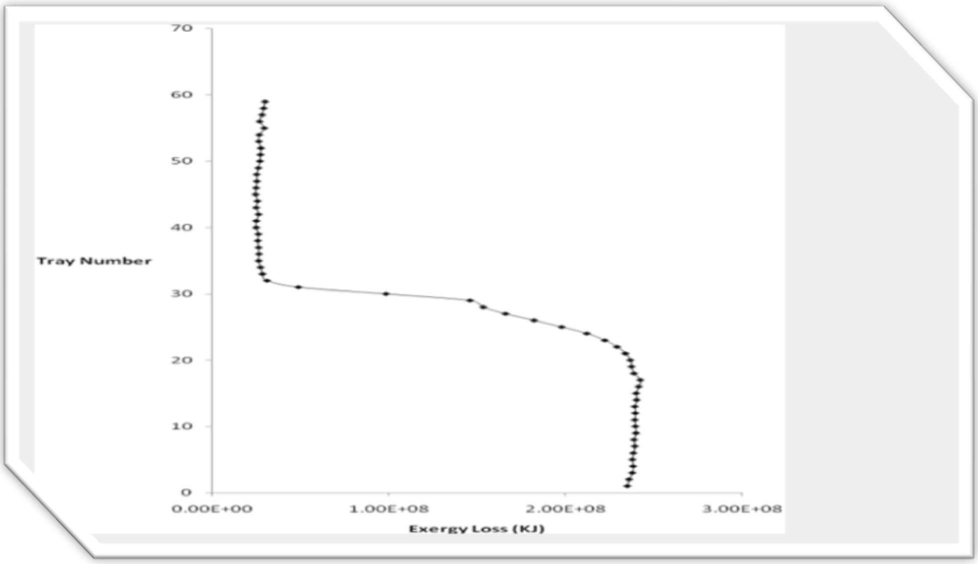


Points A, B, C are on the frontier (efficient) with DMU 1 as WEP, DMU 2 as EP, and DMU 3 as SEP

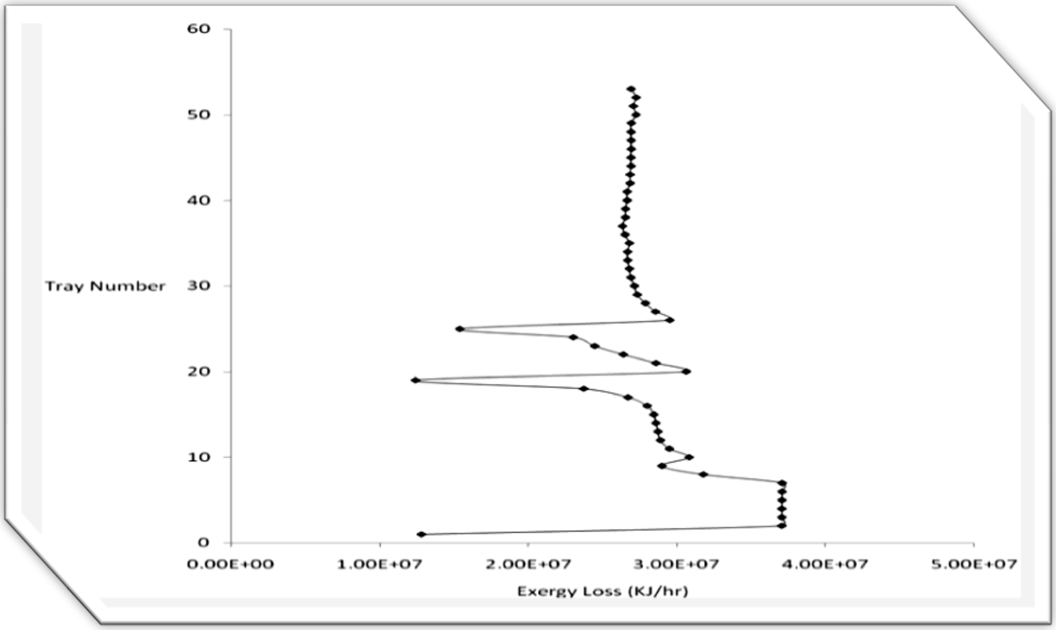
Appendix B: Exergetic rate profiles of the 18 simulated systems



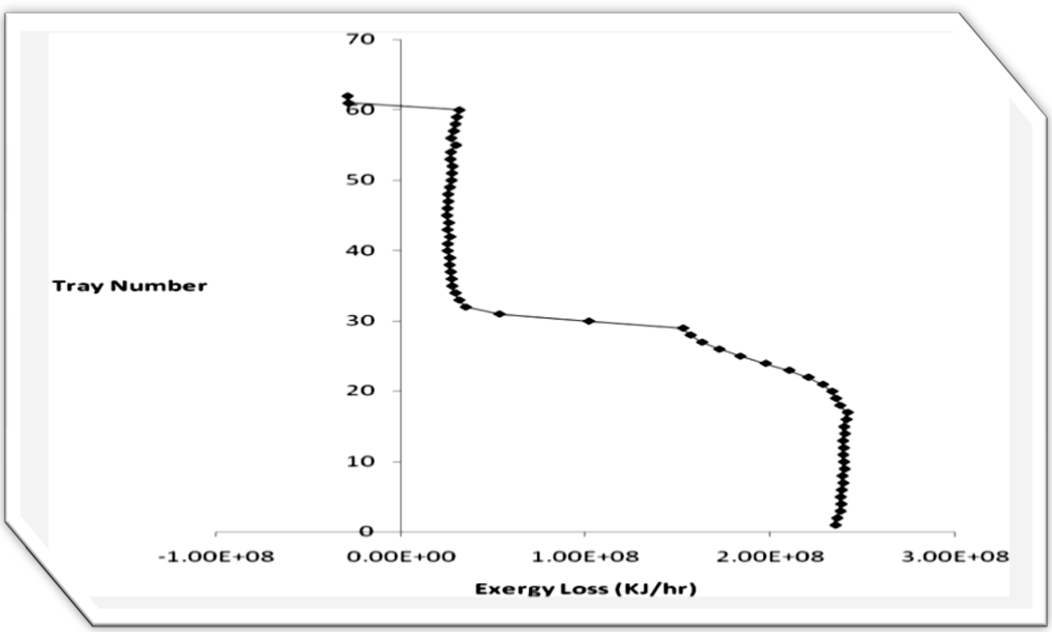
Appendix B1. Exergy destruction distribution curve for Depropanizer of the base case



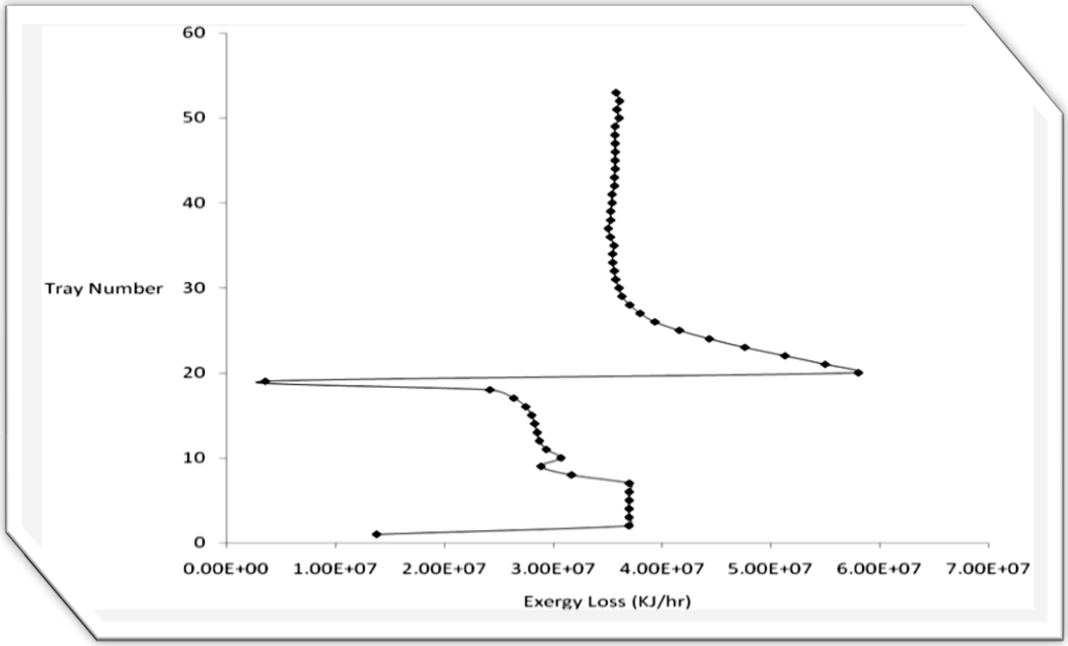
Appendix B2. Exergy destruction distribution curve for Debutanizer of the base case



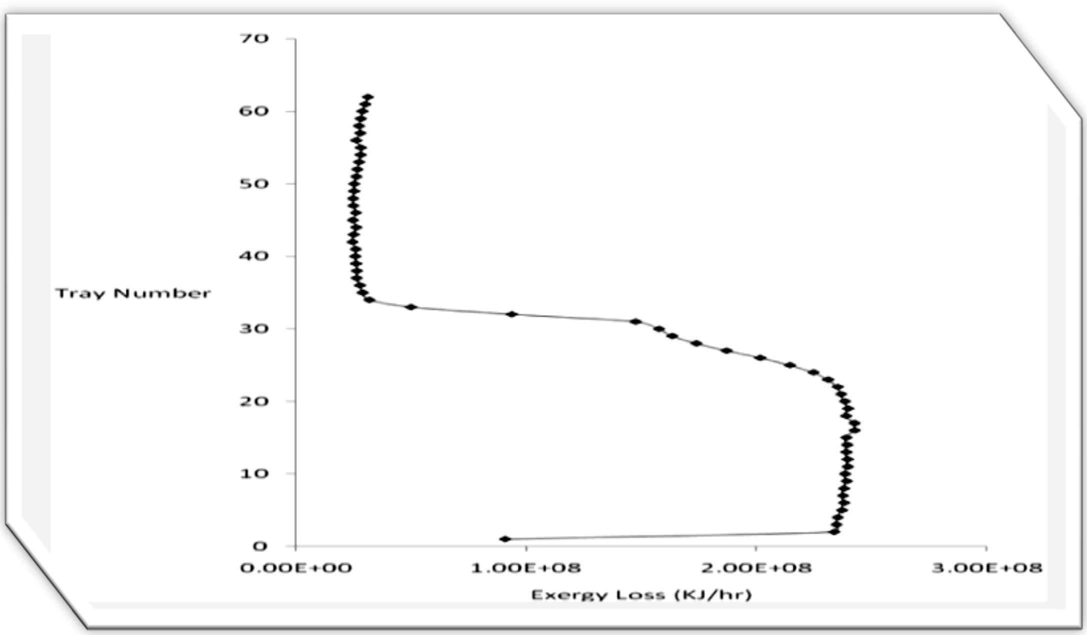
Appendix B3. Exergy destruction distribution curve for Depropanizer of the base – 30^{o}C case



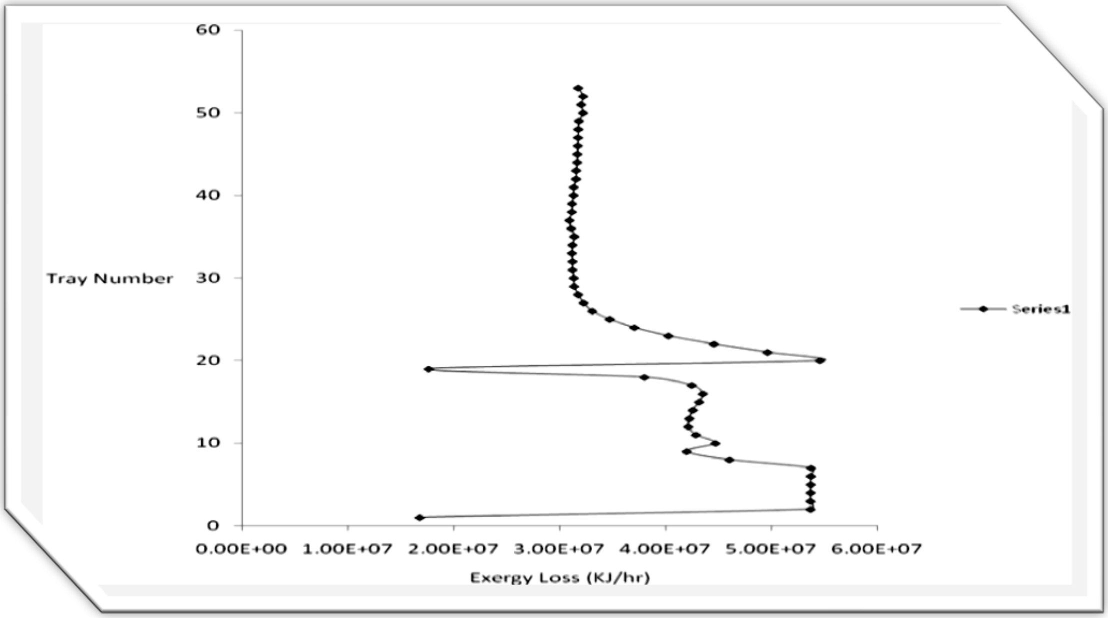
Appendix B4. Exergy destruction distribution curve for Debutanizer of the base – 30^{o}C case



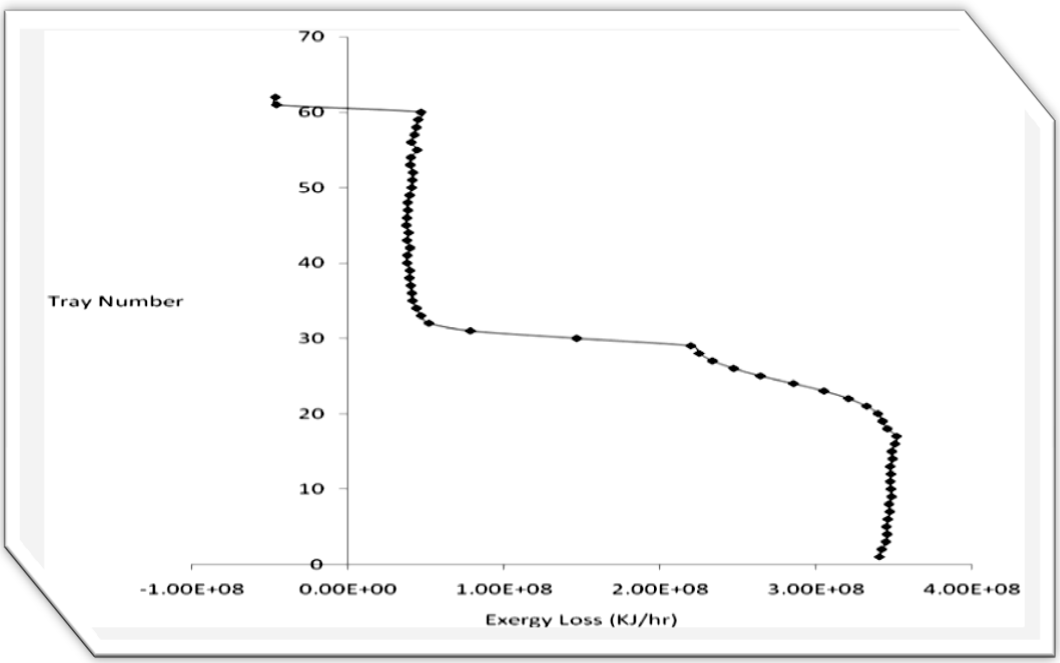
Appendix B5. Exergy destruction distribution curve for Depropanizer of the base – 80^{o}C case



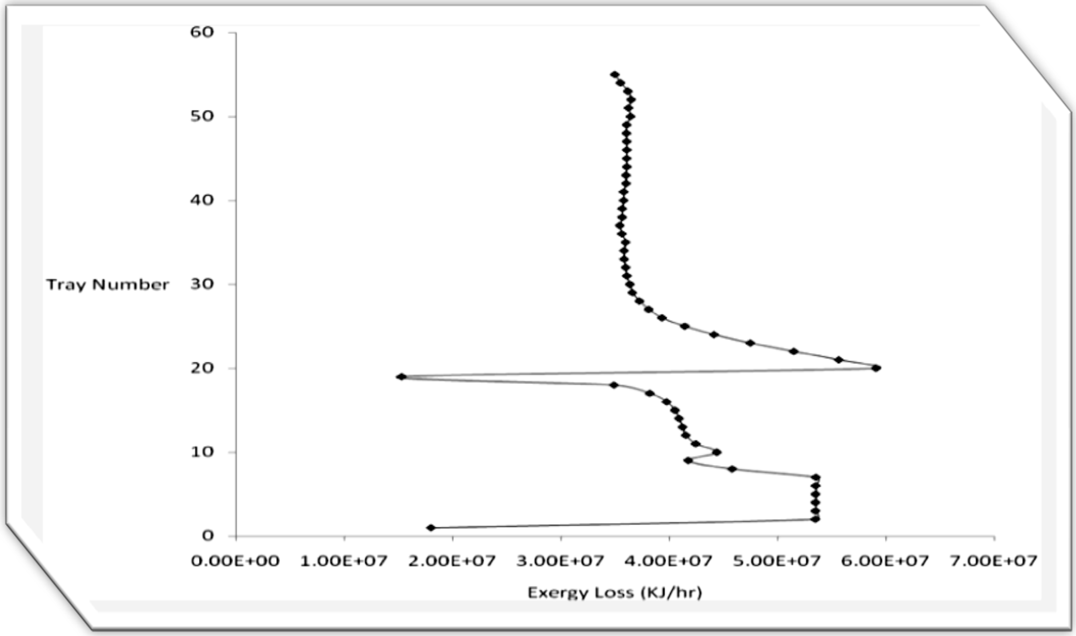
Appendix B6. Exergy destruction distribution curve for Debutanizer of the base – 80^{o}C case



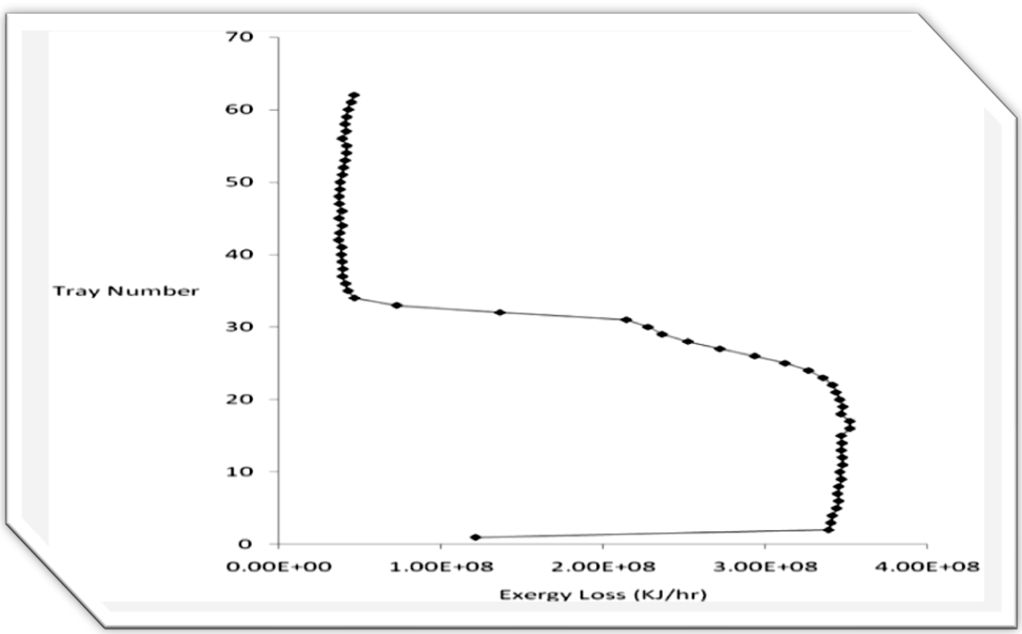
Appendix B7. Exergy destruction distribution curve for Depropanizer the base – 30^{o}C - reflux ration 6 case



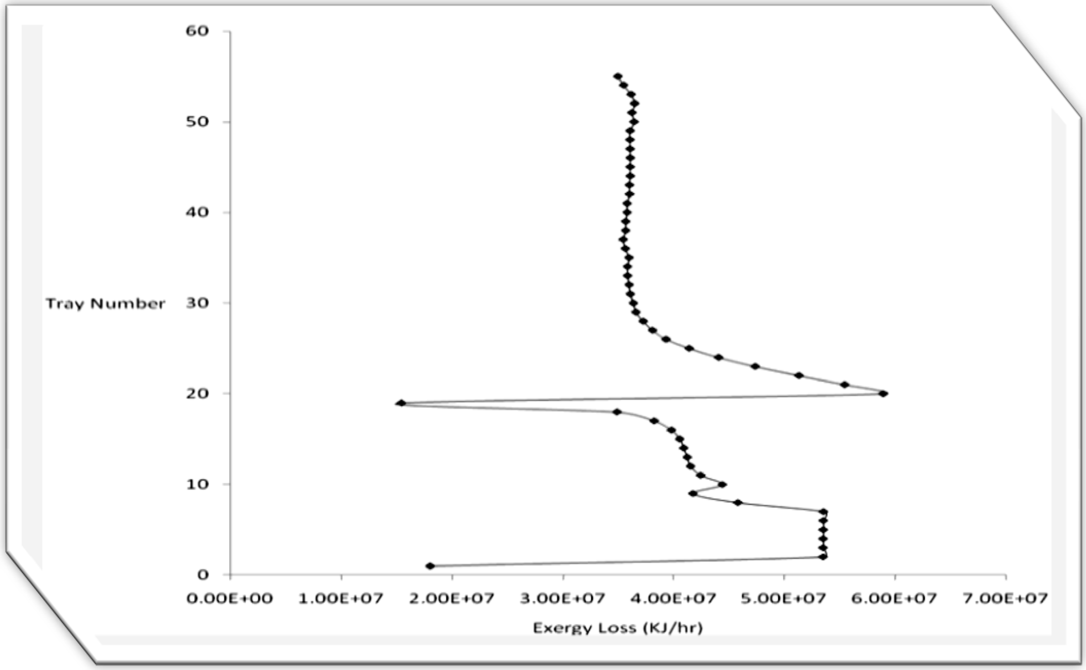
Appendix B8. Exergy destruction distribution curve for Debutanizer the base – 30^{o}C -reflux ratio 6 case



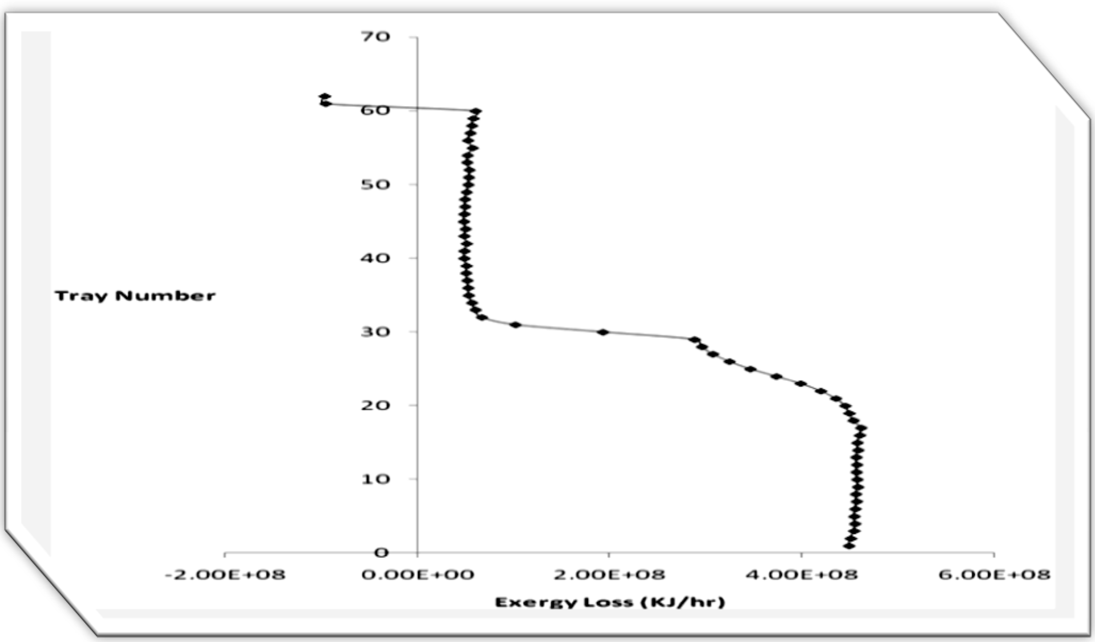
Appendix B9. Exergy destruction distribution curve for Depropanizer of the base – 80^{o}C -reflux 6 case



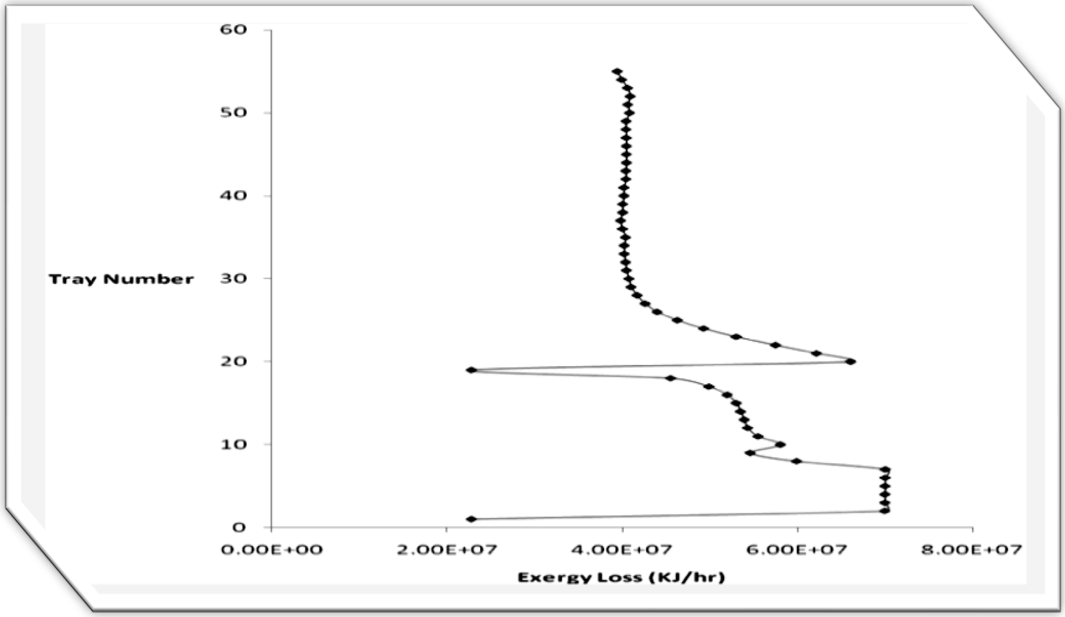
Appendix B10. Exergy destruction distribution curve for Debutanizer of the base – 80^{o}C-reflux ratio case



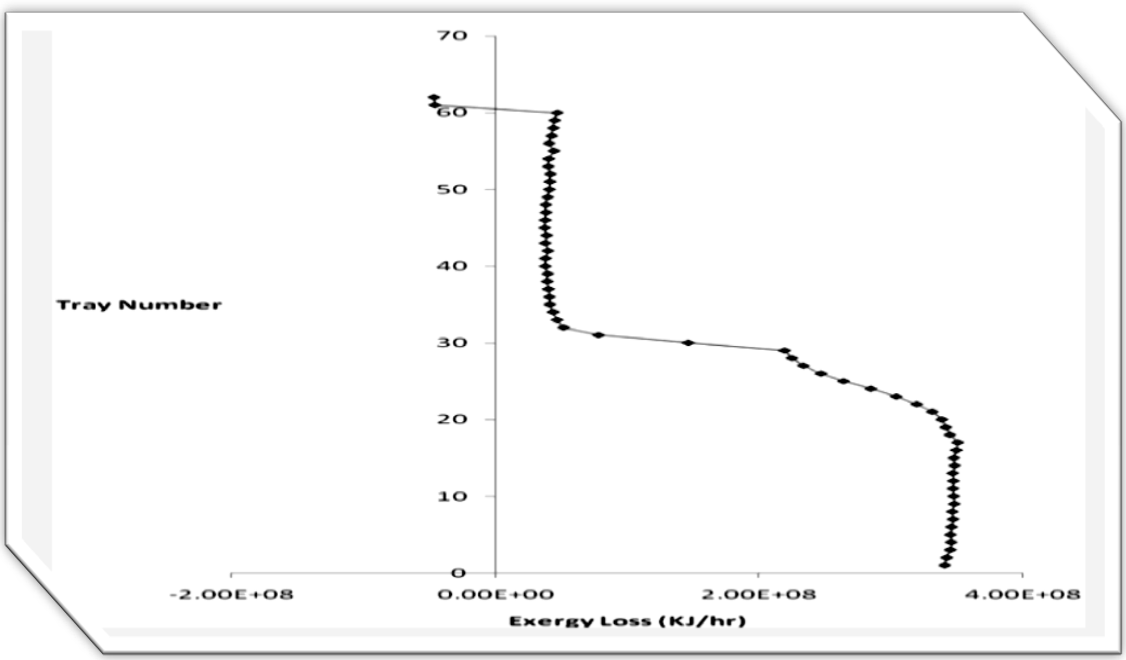
Appendix B11. Exergy destruction distribution curve for Depropanizer of the base – reflux ratio 6 case



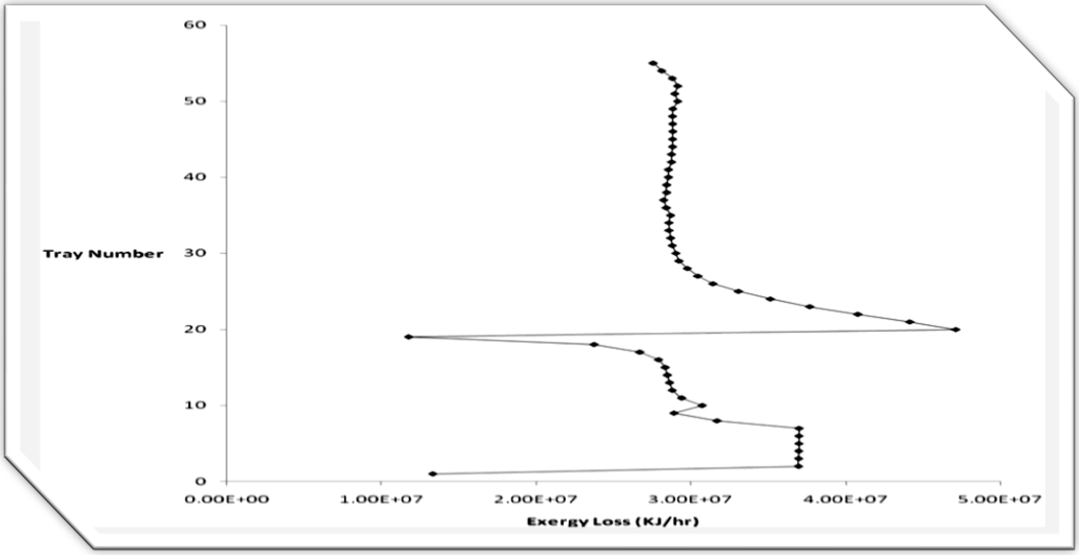
Appendix B12. Exergy destruction distribution curve for Debutanizer of the base – reflux ratio 6 case



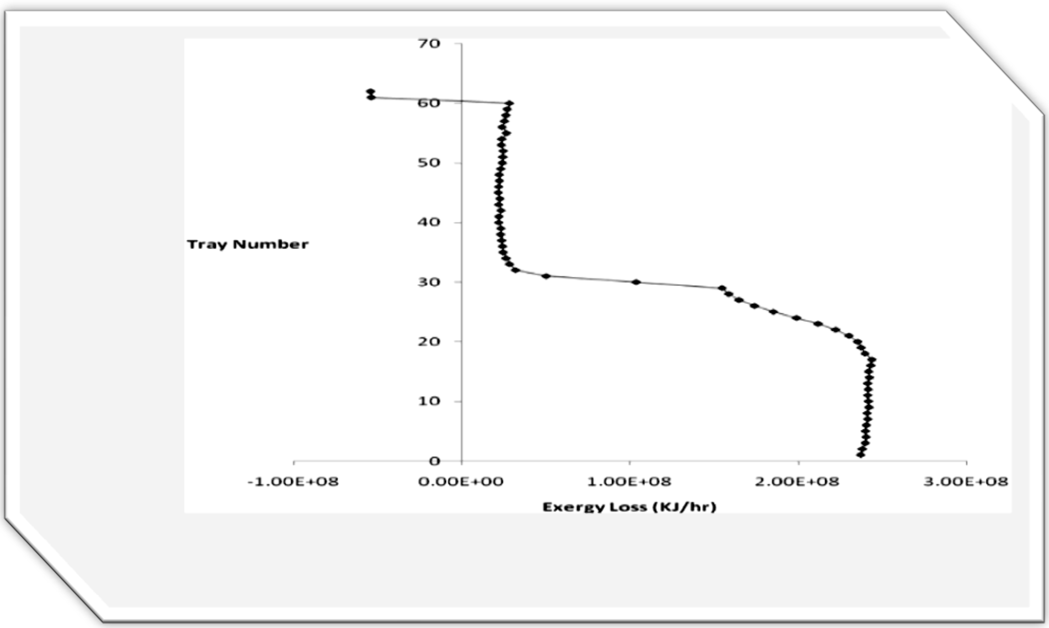
Appendix B13. Exergy destruction distribution curve for Depropanizer of the base – 1200 kPa case



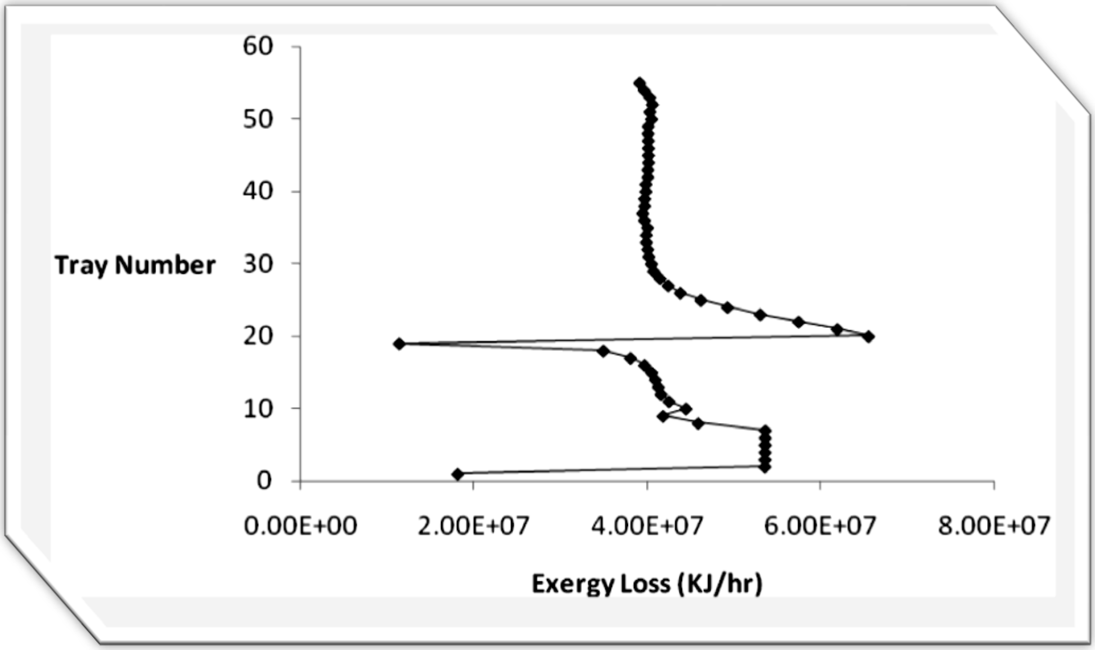
Appendix B14. Exergy destruction distribution curve for Debutanizer of the base –1200 kPa case



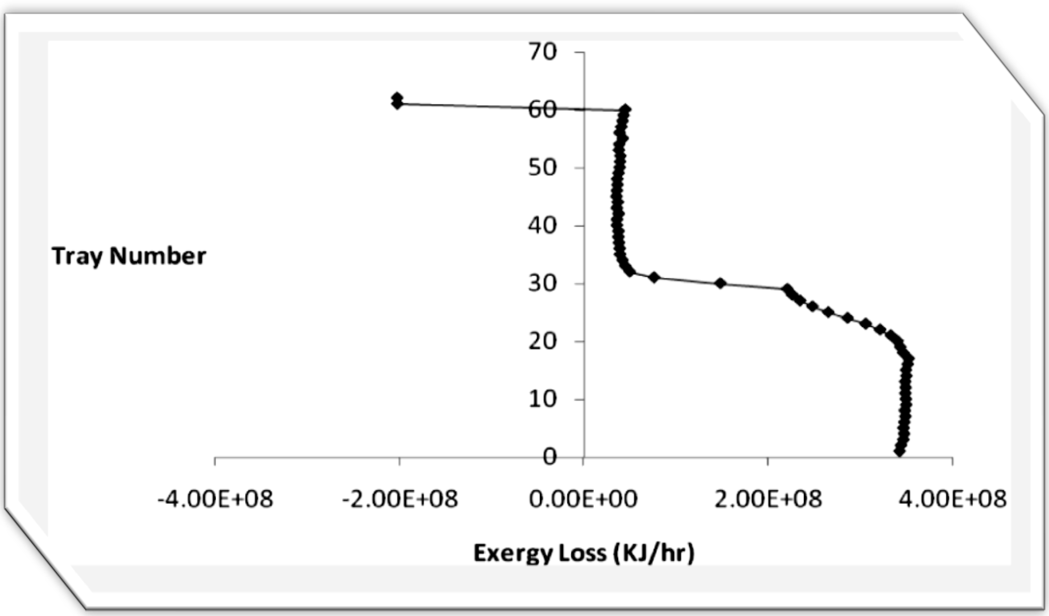
Appendix B15. Exergy destruction distribution curve for Debutanizer of the base – 1200 kPa-30°C case



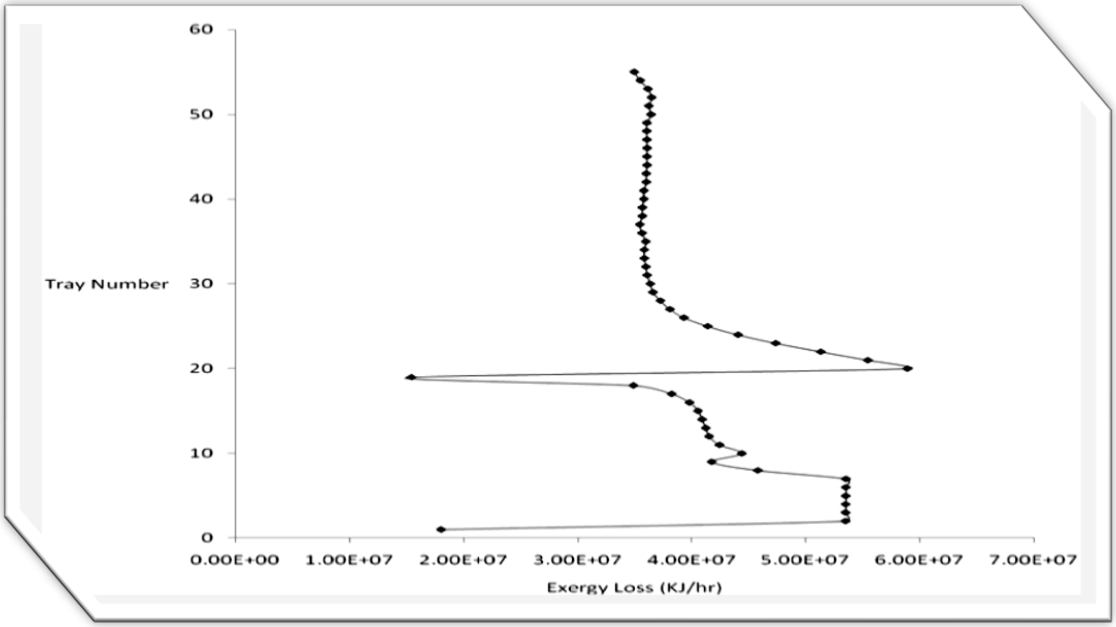
Appendix B16. Exergy destruction distribution curve for Debutanizer of the base – 1200 kPa-30°C case



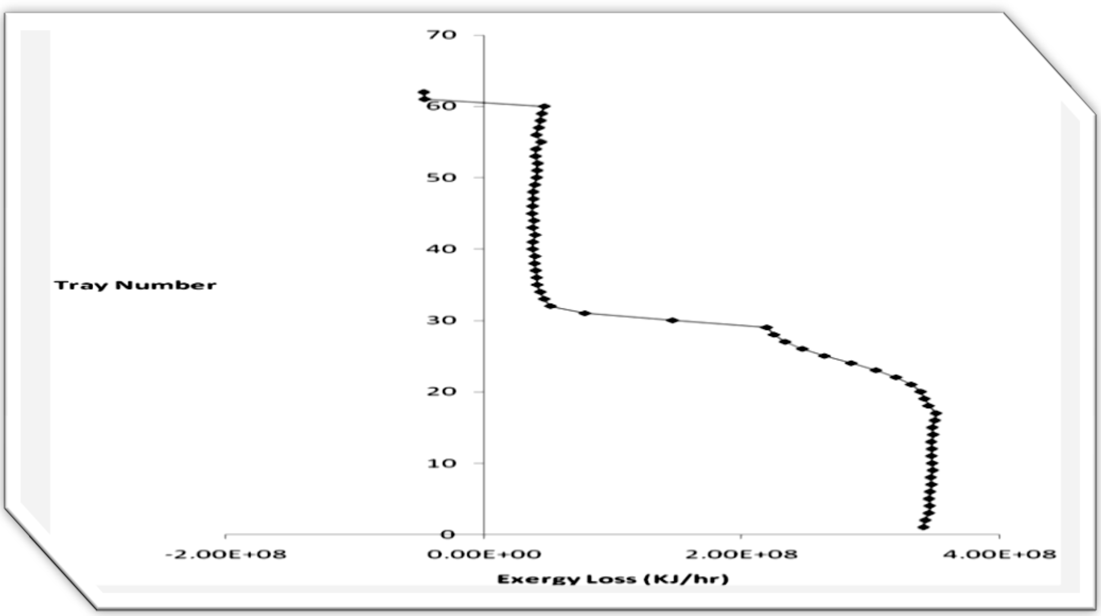
Appendix B17. Exergy destruction distribution curve for Depropanizer of the base – 1200 kPa- 80^{o}C case



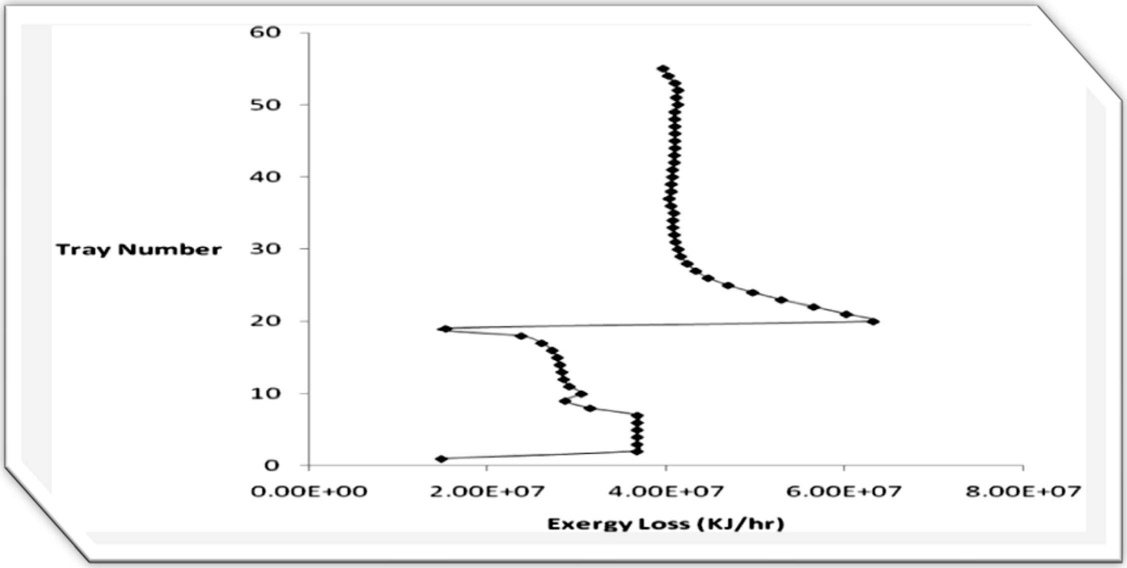
Appendix B18. Exergy destruction distribution curve for Debutanizer of the base – 1200kPa-80^{o}C case



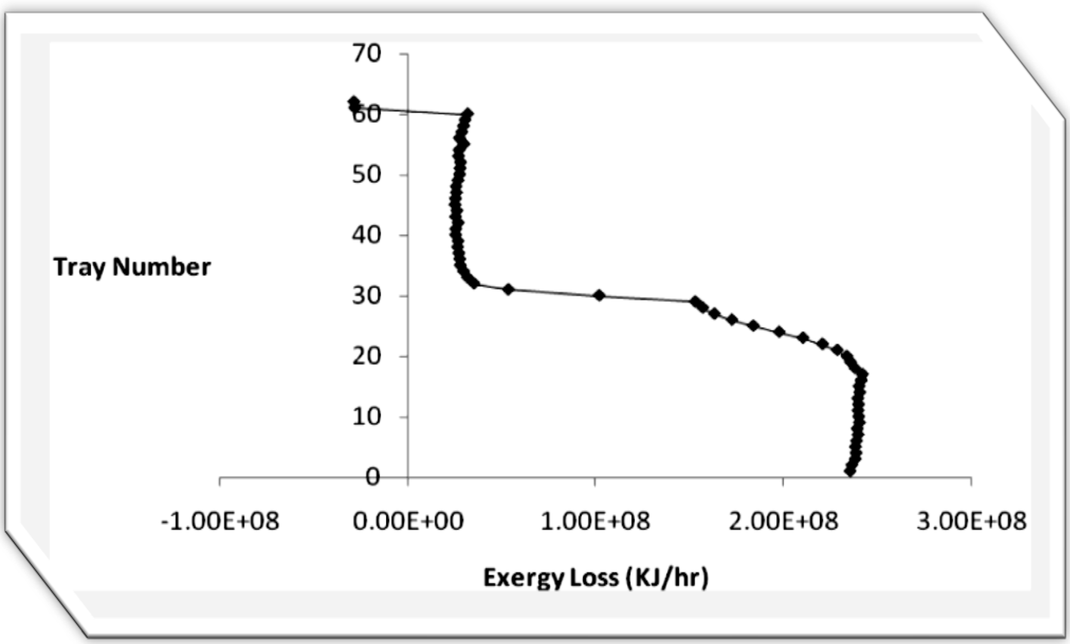
Appendix B19. Exergy destruction distribution curve for Depropanizer of the base – 1200kPa-reflux ratio 6 case



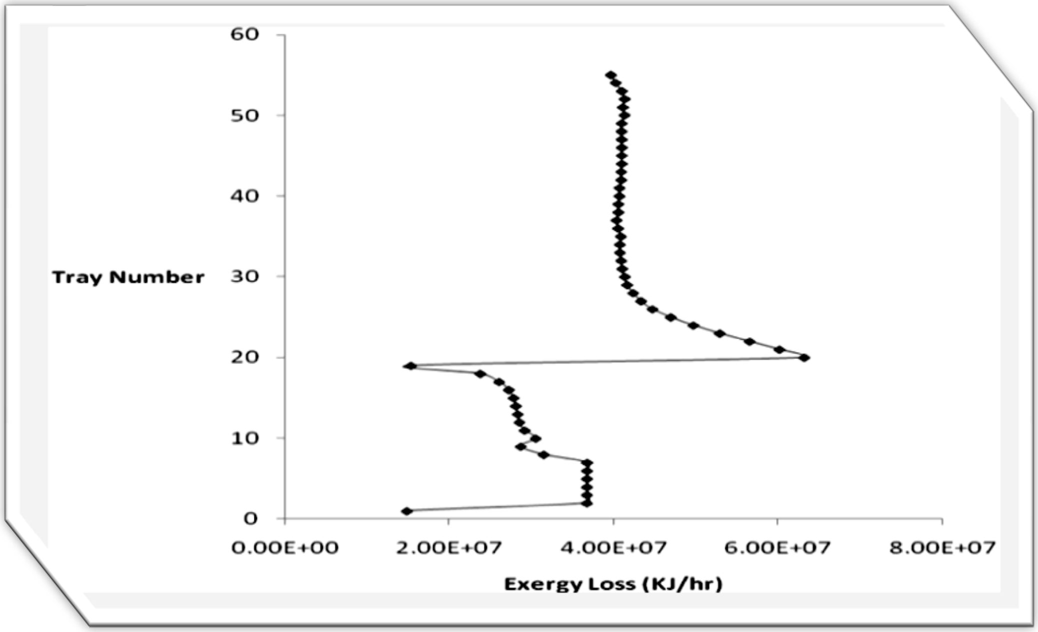
Appendix B20. Exergy destruction distribution curve for Debutanizer of the base –1200 kPa-reflux ratio 6 case



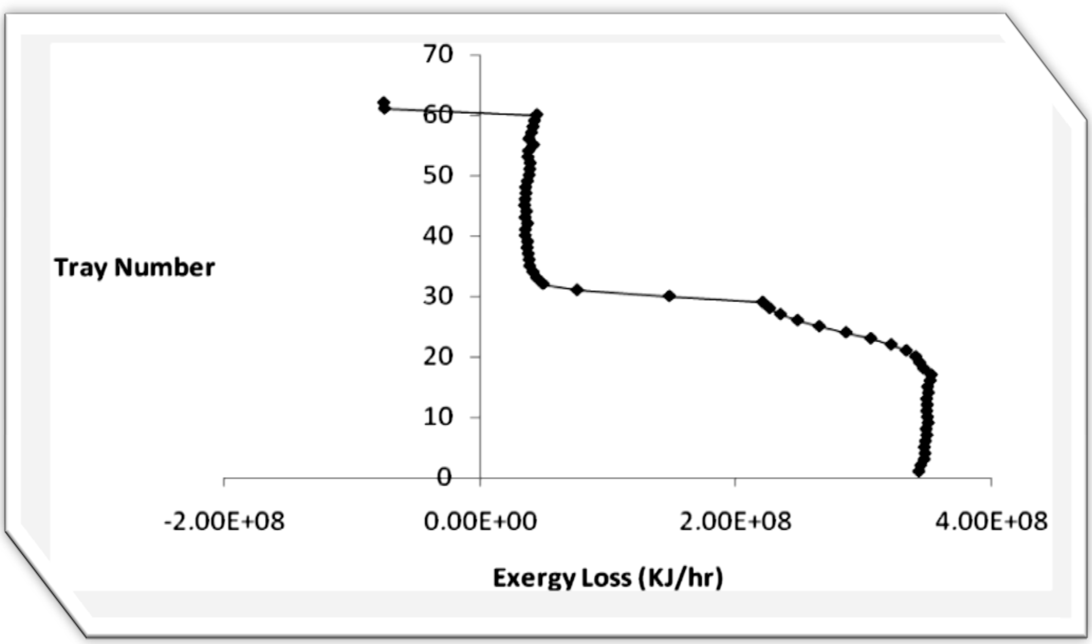
Appendix B 21. Exergy destruction distribution curve for Depropanizer of the 800 kPa case



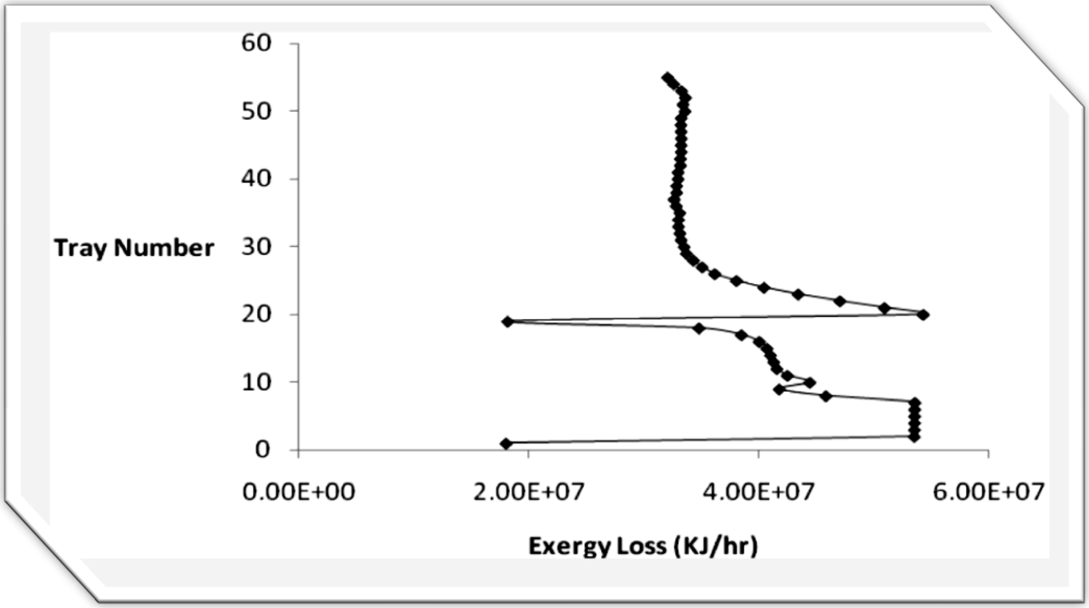
Appendix B22. Exergy destruction distribution curve for Debutanizer of the 800 kPa case



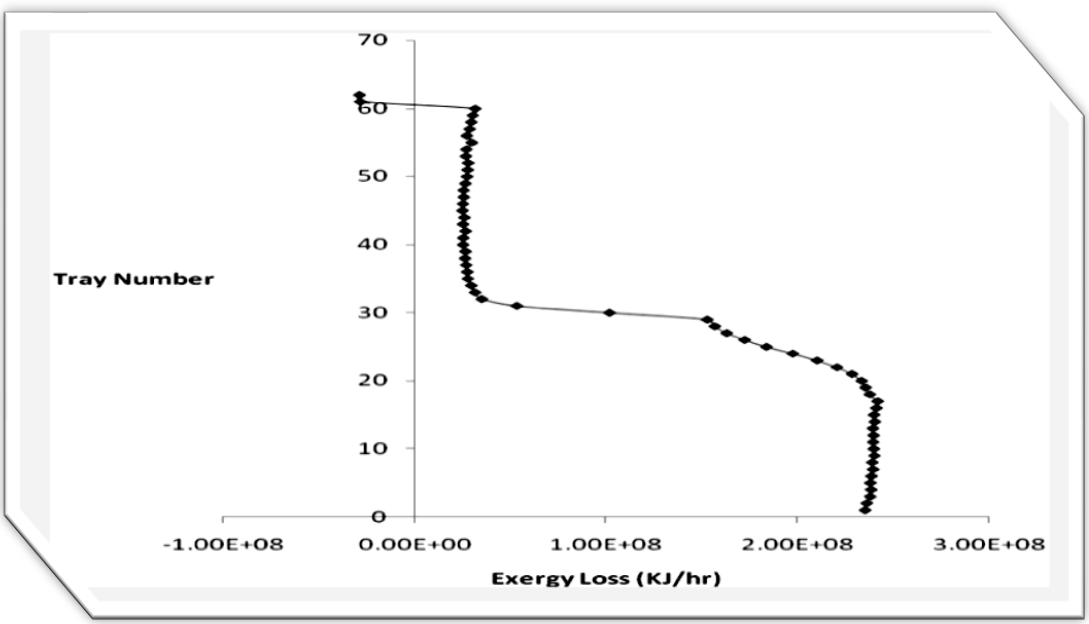
Appendix B23. Exergy destruction distribution curve for Depropanizer of the 800 kPa – 80^{o}C case



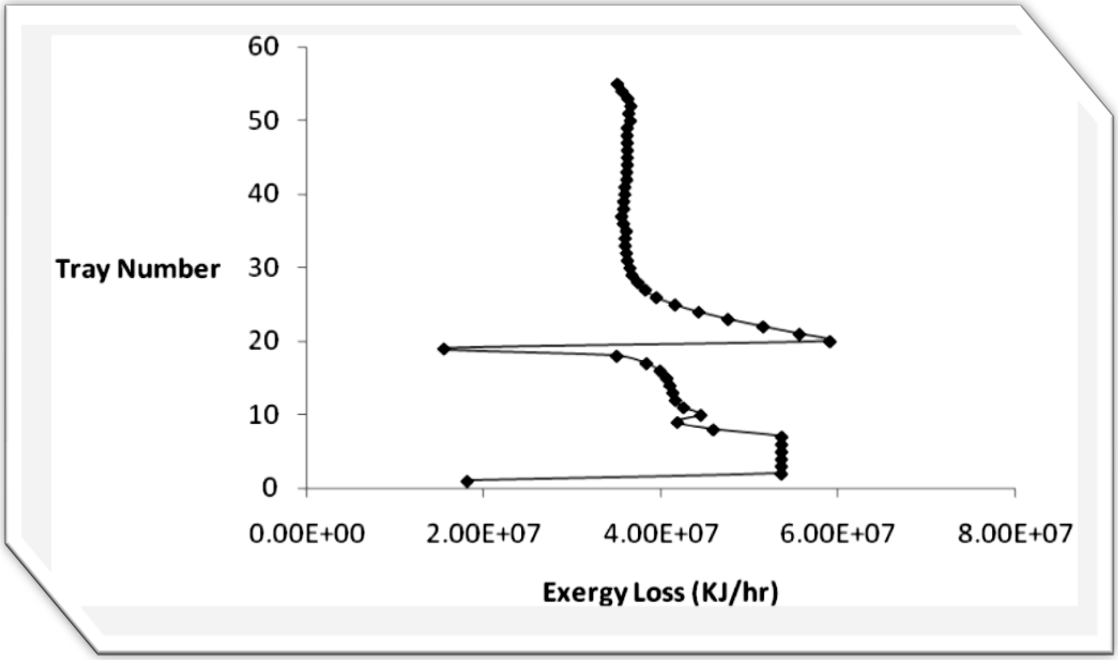
Appendix B24. Exergy destruction distribution curve for Debutanizer of the 800 kPa – 80^{o}C case



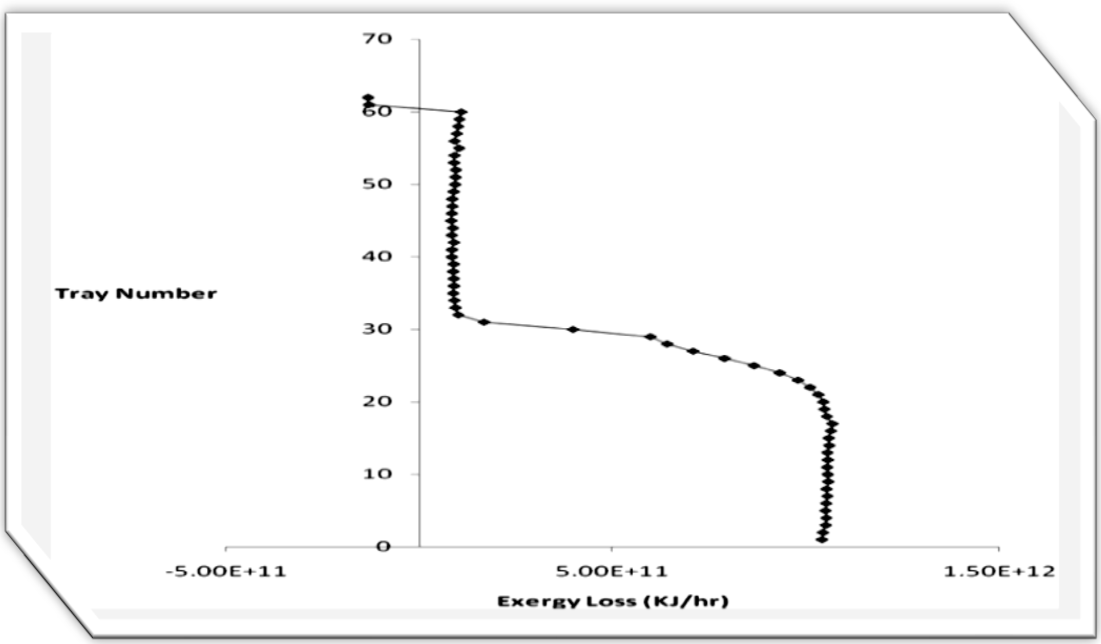
Appendix B25. Exergy destruction distribution curve for Depropanizer of the 800 kPa-30^{o}C-reflux ratio 6 case



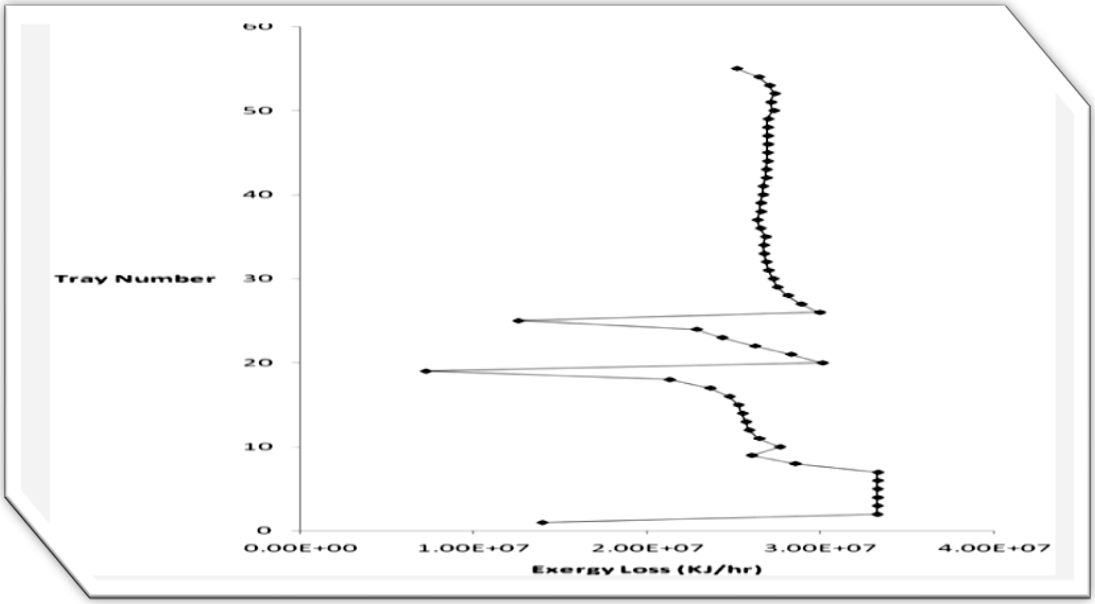
Appendix B26. Exergy destruction distribution curve for Debutanizer of the 800 kPa – 30^{o}C-reflux ratio 6 case



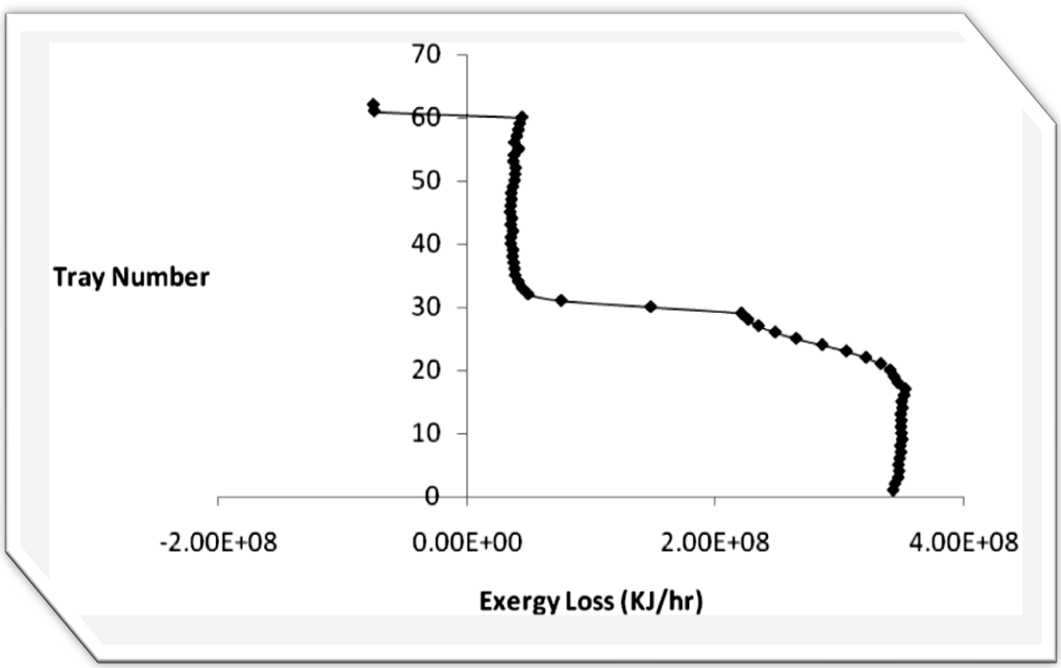
Appendix B27. Exergy destruction distribution curve for Depropanizer of the 800 kPa – reflux ratio 6 case



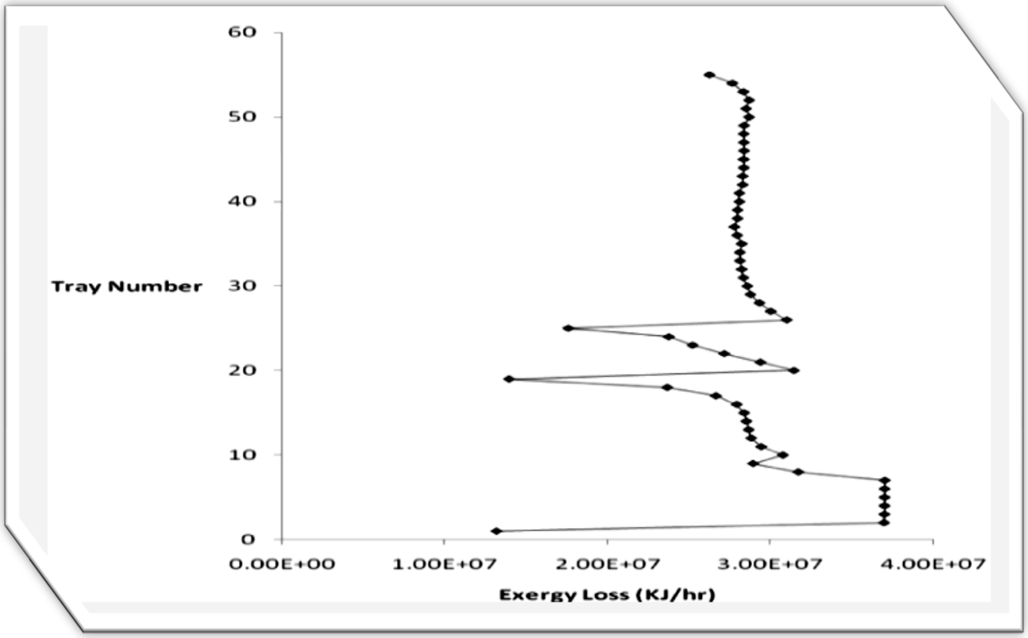
Appendix B28. Exergy destruction distribution curve for Debutanizer of the 800 kPa – reflux ratio 6 case



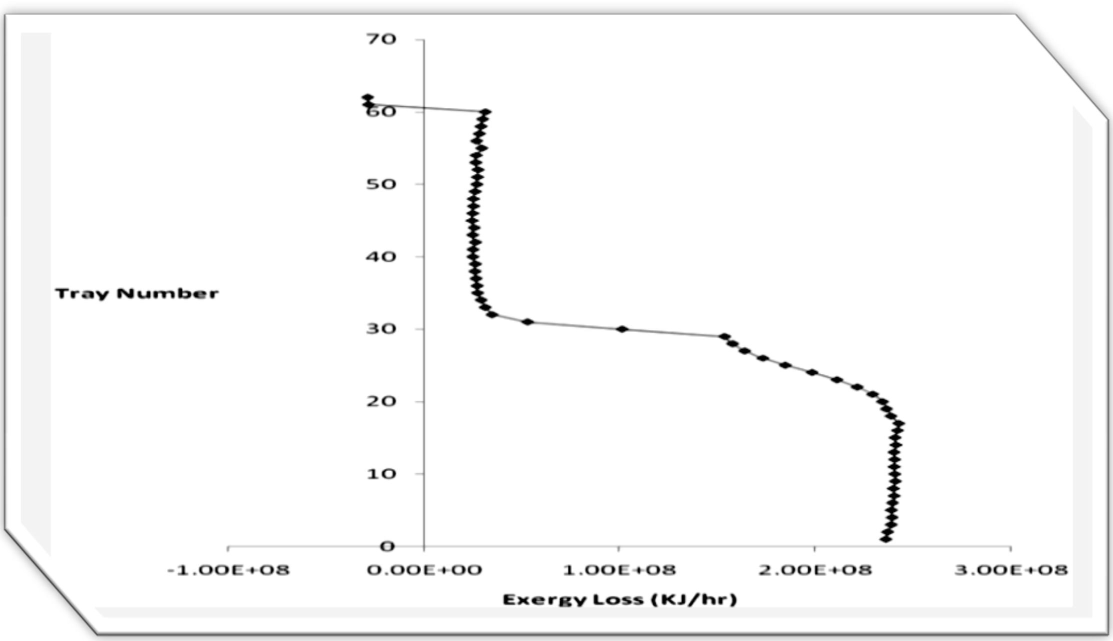
Appendix B29. Exergy destruction distribution curve for Depropanizer of the splitted feed case



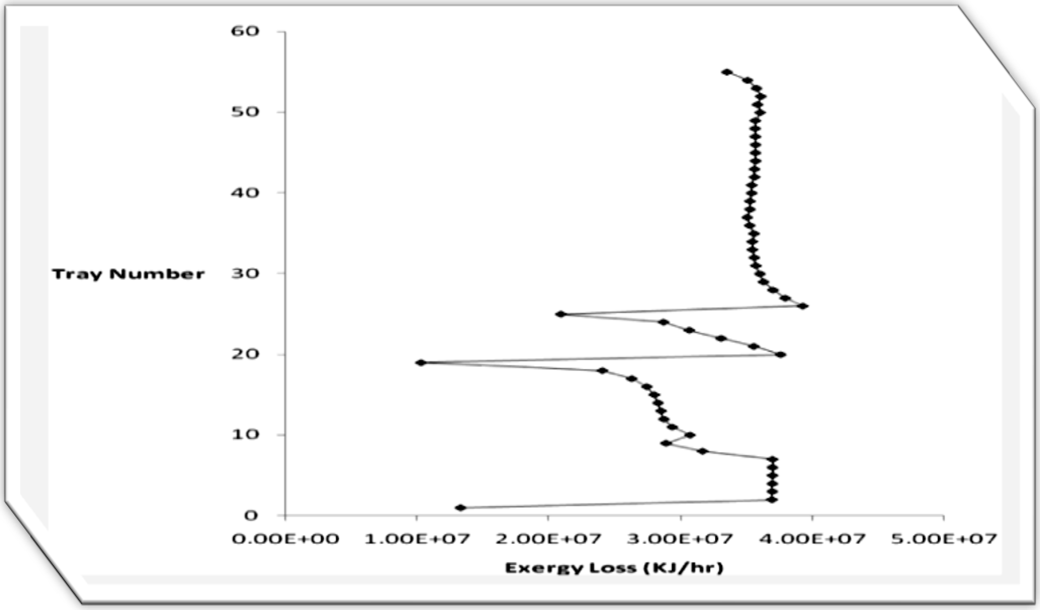
Appendix B30. Exergy destruction distribution curve for Debutanizer of the splitted case



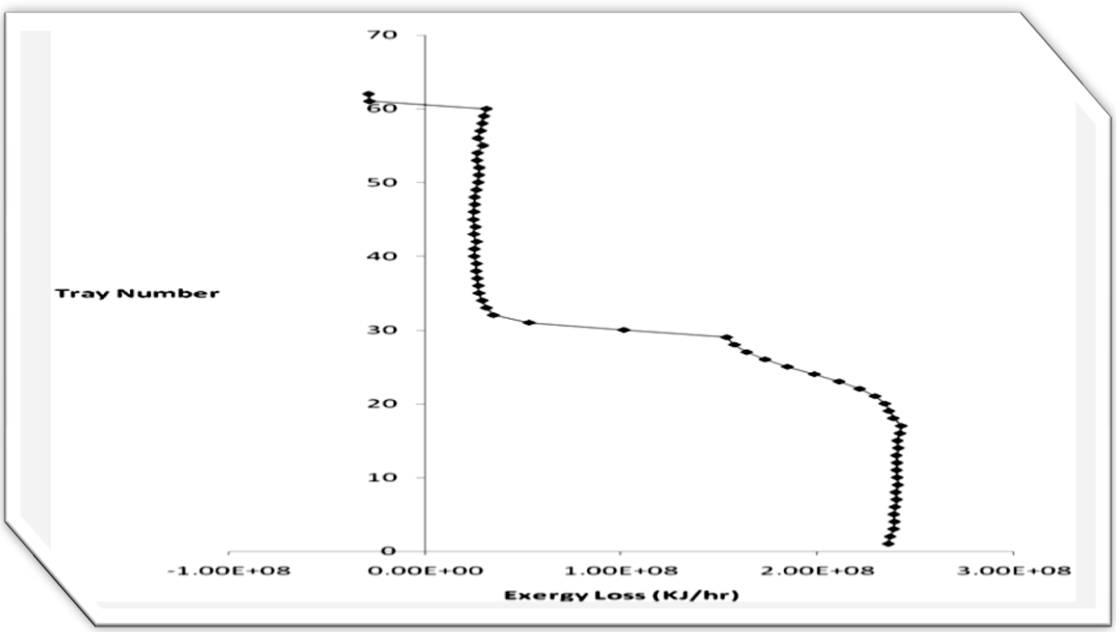
Appendix B31. Exergy destruction distribution curve for Depropanizer of the splitted feed – 30°C case



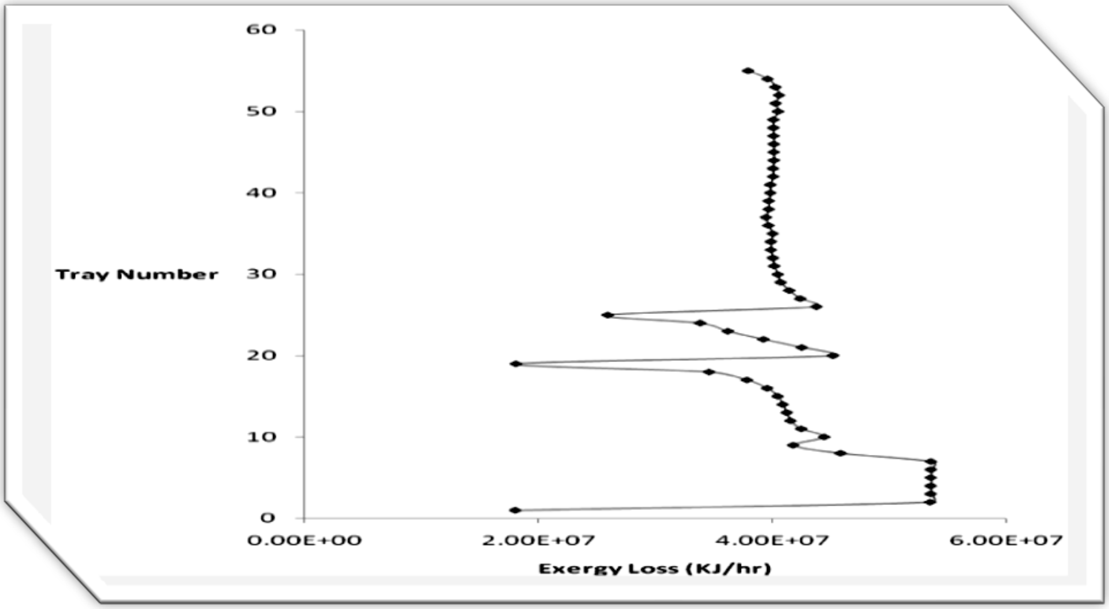
Appendix B32. Exergy destruction distribution curve for Debutanizer of the splitted feed – 30°C case



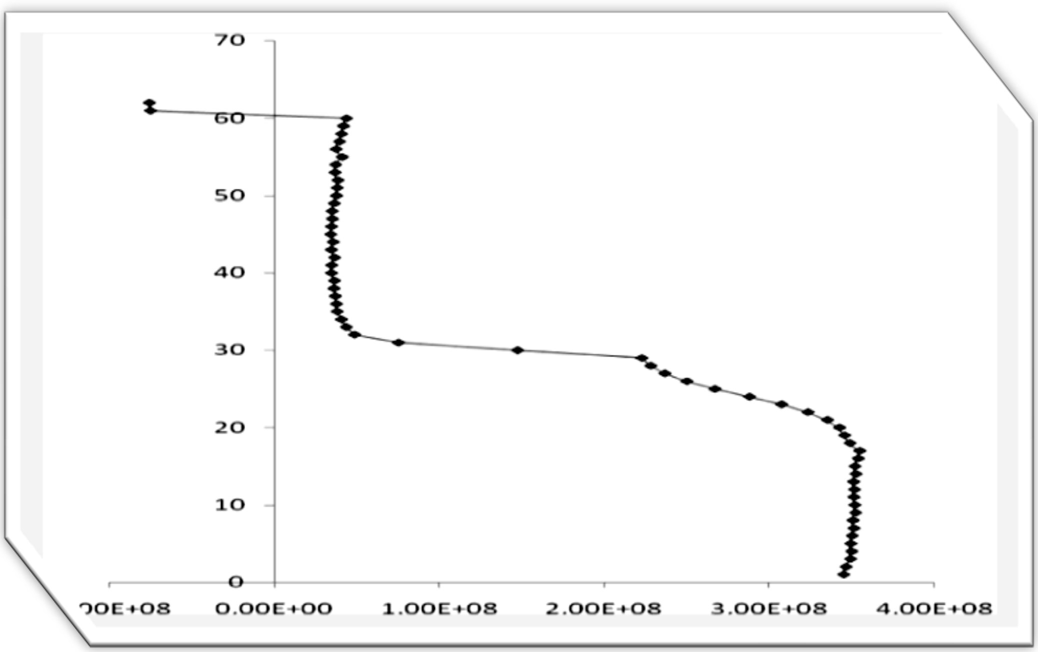
Appendix B33. Exergy destruction distribution curve for Depropanizer of the splitted feed – 80^{o}C case



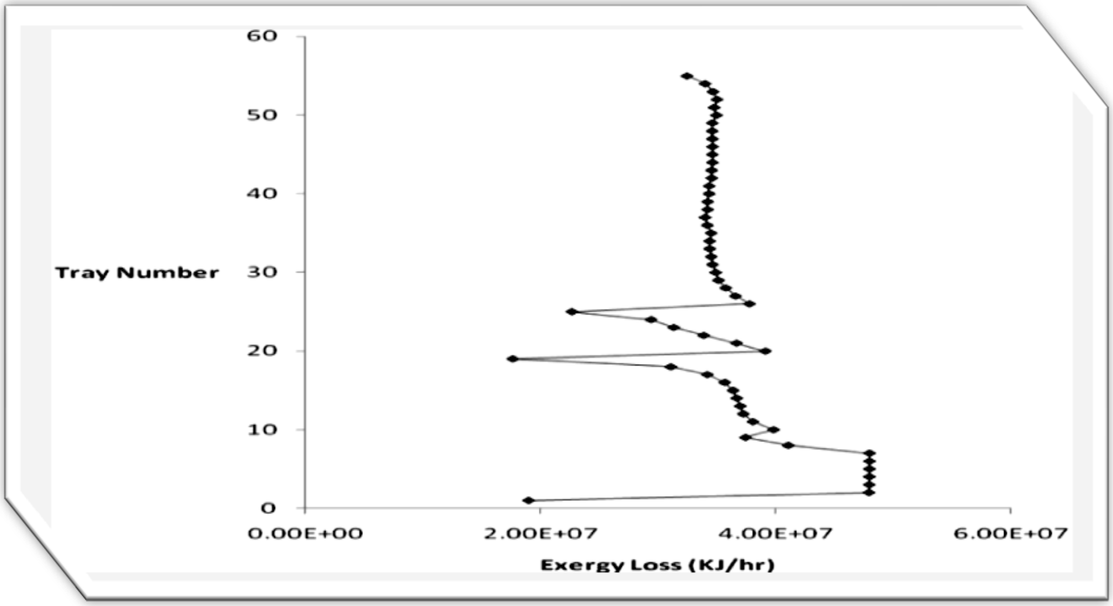
Appendix B34. Exergy destruction distribution curve for Debutanizer of the splitted feed– 80^{o}C case



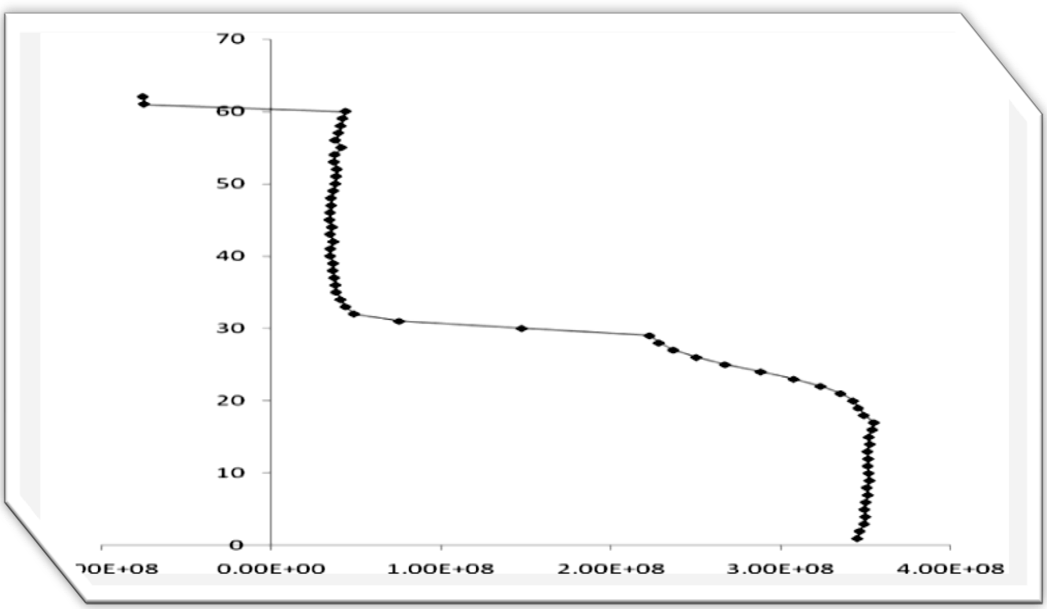
Appendix B35 Exergy destruction distribution curve for Depropanizer of the splitted feed – 80^{o}C-Reflux ratio 6 case



Appendix B36. Exergy destruction distribution curve for Debutanizer of the splitted feed –Reflux ratio 6 case



Appendix B37. Exergy destruction distribution curve for Depropanizer of the splitted feed –Reflux ratio 6 case



Appendix B38. Exergy destruction distribution curve for Debutanizer of the splitted feed –Reflux ratio 6 case