International Journal of Industrial Engineering & Production Research March 2021 Vol. 32, No. 1: 47-64
DOI: 10.22068/ijiepr.32.1.47

RESEARCH PAPER

A DEA Approach to Measuring Teammate-Adjusted Efficiencies Incorporating Learning Expectations: An Application to Oil & Gas Wells Drilling

Hessam Nedaei[1], Seyed Gholamreza Jalali Naini[2*] & Ahmad Makui[3]

Received 28 March 2020; Revised 17 September 2020; Accepted 21 September 2020;

ABSTRACT
Data Envelopment Analysis (DEA) measures the relative efficiency of Decision-Making Units (DMUs) with multiple inputs and multiple outputs. In the case of considering a working team as a DMU, it often comprises multiple positions with several employees. However, there is no method to measure the efficiency of employees individually taking account the effect of teammates. This paper presents a model to measure the efficiency of employees such that they are fairly evaluated regarding relative performances of their teammates. Moreover, the learning expectations and the effect of learning lost due to operation breaks are incorporated into the DEA model. This model is thus able to rank the employees working in each position that can then be utilized within award systems. The capabilities of the proposed model are then explored by a case study of 20 wells with 160 distinct operations in the South Pars gas field, which is the first application of DEA in the oil and gas wells drilling performance analysis.

KEYWORDS: *Data envelopment analysis; Teammate efficiency; Learning; Oil and gas; Drilling.*

1. Introduction

Oil and gas drilling projects, which are one of the groundworks of world economy, utilize more than 250 offshore and 900 land drilling rigs worldwide [1]. Several employees including those related to the operator, rig contractor, and service companies are involved in drilling operations. Execution of these projects requires rotation schemes that could be very variable for different positions. For instance, projects may confront rotation schemes such as four weeks on, four weeks off; six weeks on, three weeks off; eight weeks on, four weeks off; or even twenty weeks on, four weeks off [2]. The combinations of the rotational personnel construct various groups that ultimately run drilling operations. These operational groups of employees are essential to the success of drilling projects. Besides, returns on investment in the oil and gas sector have considerably decreased since 2007. Even at a time of 100 USD/bbl oil price, numerous operators had difficulties in meeting their commitments. Since the oil price has halved, it is more evident than any other time that there is an essential requirement for operators to reduce their costs. It has been revealed that rigorous performance management could reduce up to 5 percent to 10 percent of a well's cost [3]. Such performance data could be measured by the well-known approach of Data Envelopment Analysis (DEA), which is a technique for measuring the relative efficiency of a set of Decision-Making Units (DMUs) that apply multiple inputs to produce multiple outputs. Since the groundbreaking work of Charnes et al. [4], various studies expressing the methodology and application of DEA have been published as reviewed in a 30-year survey of Cook and Seiford [5], a 40-year survey and bibliography of Emrouznejad and Yang [6], and a review of efficiency-ranking methods of Aldamak and Zolfaghari [7].

In the oil and gas industry, many operator companies apply learning curves in their cost-estimating guidelines [8]. Applying the learning curve concept to operations management has numerous benefits including setting more

* Corresponding author: *Seyed Gholamreza Jalali Naini*
sgjalali@iust.ac.ir

1. *Department of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran.*
2. *Department of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran.*
3. *Department of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran.*

accurate operational standards, predicting operation output, identifying non-conforming units, and competitive pricing [9]. Learning curves provide a mathematical representation of the learning process that takes place as activity repetition occurs over a period of time [10,11]. These curves were initially proposed by Wright [12] by detecting cost reduction after conducting repetitive tasks in production plants.

As discussed by Mislick and Nussbaum [13], operation breaks take place when a system yields some output and operation suddenly terminates. Generally, the longer the break, the greater loss of learning for employees, as they forget the processes that they had learned. Mislick and Nussbaum [13] also presented the steps required to specify how much learning was achieved and how much was then lost.

The learning effect can be considered in the DEA models as an external factor. For instance, Chang et al. [14] and Lyu et al. [15] presented a DEA model that incorporates the estimation of a learning effect as an external parameter. Although they have included the learning effect in their model, they have not considered lost learning in the case of an operational break.

Ang et al. [16] developed group efficiency and group cross-efficiency models to evaluate Taiwan hotel chains and subsidiary hotels. They also presented a definition for the average performance that considers group efficiency as the average of its members' performance. Their models focus on the performance of hotel chains from the view of the group rather than individual hotels. However, their model does not measure the efficiencies in a more complicated structure of groups, e.g., those derived from employee rotation schemes.

To overcome the mentioned limitations, this paper develops a DEA model which is able to measure adjusted efficiencies based on teammates' performance levels in a system consisting of multiple positions with employees working in rotation schemes. This model is thus able to rank the employees working in each position that can then be utilized within award systems. Moreover, although many authors have applied DEA in energy and environment in the past four decades as reviewed by Sueyoshi et al. [17], DEA has not been utilized for measuring the drilling efficiency of oil and gas wells. Therefore, the present paper is the first application of DEA in the case of oil and gas wells drilling performance analysis.

This paper proceeds to investigate the research question of how to measure the teammate-adjusted efficiency of employees in a multi-position system. More specifically, related to our case study, the aim is to answer the following questions: "what are the ranks of the drilling supervisors and directional drillers in the drilling operations of 20 wells in the South Pars gas field considering teammates' performances and learning expectations?"

The remainder of this paper is organized as follows. Section 2 introduces the proposed model. Section 3 illustrates the application of the model in the case of oil and gas wells drilling. Finally, Section 4 concludes the discussion.

2. Proposed Model

As discussed in the introduction, in the case of considering working teams as DMUs, they often comprise multiple positions with several employees. In addition, the combinations of the rotational personnel construct several groups of employees that ultimately run distinct drilling operations. In this case, the management team has more interest to focus on the overall performance of each employee instead of the performance of a specific piece of operation. In this regard, we provide a definition for employee efficiency. Then, we further the evaluation by measuring the efficiency related to the two-person combinations and the groups of employees. To frame the development of these models, we consider n distinct operations as the DMUs within the proposed model. These operations are conducted by a group of K positions with H_p employees for each position p, $p = 1,\ldots,K$. We also consider each DMU_j, $j=1,\ldots,n$, that deals with s outputs Y_{rj} and m inputs X_{ij}.

Fig. 1 depicts the structure of a DMU constructed by multiple positions.

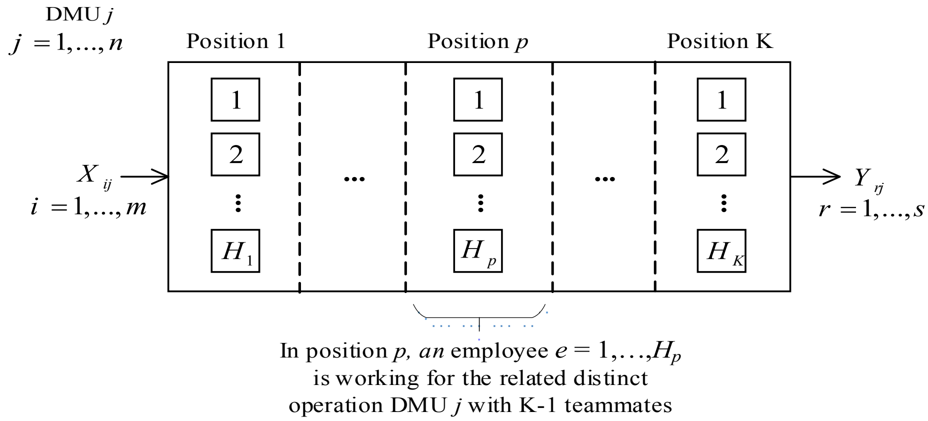

Fig. 1. Structure of a DMU constructed by multiple positions

As mentioned in the DMU structure, a single employee is working for each position. Therefore, we will have a K-person group of employees for each DMU with K positions.

A list of all indices, parameters, and variables used in the model is given in the nomenclature section.

Nomenclature

Indices

i	inputs, $i = 1,\ldots,m$
r	outputs, $r = 1,\ldots,s$
j	DMUs, $j = 1,\ldots,n$; distinct operations
p	positions in a DMU, $p = 1,\ldots,K$
e	employees in a position, $e = 1,\ldots,H_p$
t	two-person combinations of employees working in distinct operations, $t = 1,\ldots,T$
g	groups of employees related to all positions working in distinct operations, $g = 1,\ldots,G$

Parameters

X_{ij}	input values for input i in DMU j
Y_{rj}	output values for output r in DMU j
α_j^{ep}	presence of employee e of position p in distinct operation DMU j
α_j^t	presence of two-person combination t in distinct operation DMU j
α_j^g	presence of group g in distinct operation DMU j
β_g^{ep}	presence of employee e of position p in group g
$\gamma_{ep,j}^{e'p'}$	presence of employee e' of position p' in DMU j while his/her teammate employee e of position p is not present in the same operation of DMU j
L_c	Expected learning achieved in the operation sequence c

Variables

v_i	multiplier variables related to inputs i
u_r	multiplier variables related to outputs r
E^{ep}	efficiency score of employee e of position p
E^t	efficiency score of two-person combination t
E^g	efficiency score of group g
E_j^{ep}	efficiency score of distinct operation DMU j measured by employee e of position p
$R_{ep}^{e'p'}$	efficiency ratio of teammate e' of position p' against employee e of position p
$\hat{v}_p$	multiplier variables related to teammate a
$\hat{u}$	multiplier variables related to efficiency score of the associated group
E_{adj}^{ep}	adjusted efficiency score of employee e of position p

To measure the teammate-adjusted efficiency of employees, the model is proposed with two steps as follows.

2.1. Step 1

Let X_{ij} and Y_{rj} denote the i^{th} input, $i=1,...,m$, and r^{th} output, $r=1,...,s$, of the j^{th} DMU, $j=1,...,n$, respectively. To measure the efficiency of DMU o, the input-oriented multiplier form of the CCR model proposed by Charnes et al. [4] under the assumption of constant returns to scale is formulated as follows:

$$
\begin{aligned}
& E_o = \max \sum_{r=1}^{s} u_r Y_{ro} && \text{(optimization for each DMU } o=1,\dots,n\text{)} \\
& s.t. \\
& \sum_{i=1}^{m} v_i X_{io} = 1, && \\
& \sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \le 0, && j=1,\dots,n \\
& v_i, u_r \ge 0, && i=1,\dots,m,\ \ r=1,\dots,s
\end{aligned} \tag{1}
$$

where v_i and u_r are the multiplier variables of input *i* and output *r*, respectively.

The employees' performance is measured by the efficiency of distinct operations in which they have worked. Therefore, the performance of an employee can be considered as the average of the related operations' performances. We define employee efficiency in the following.

Definition 1 The efficiency of employee *e*, *e* = 1,…,H_p, of position *p*, *p* = 1,…,*K*, denoted by E^{ep}, is as follows:

$$
E^{ep} = \frac{1}{\sum_{j=1}^{n} \alpha_j^{ep}} \left(\sum_{j=1}^{n} \alpha_j^{ep} \frac{\sum_{r=1}^{s} u_r^{ep} Y_{rj}}{\sum_{i=1}^{m} v_i^{ep} X_{ij}} \right) \tag{2}
$$

where α_j^{ep} is a binary matrix representing the presence of employee *e* of position *p* in distinct operation DMU *j*; thus, $\sum_{j=1}^{n} \alpha_j^{ep}$ equals the number of distinct operations in which employee *ep* has worked.

The efficiencies of DMUs for which employee *ep* has worked are expressed by common weights of (v_i^{ep}, u_r^{ep}). Since the employee is present in all the related distinct operations and the efficiency is measured from this employee's point of view, a common weight bundle is utilized within groups of operations in which the employee has worked. This is similar to the group efficiency proposed by Ang et al. [16]. The optimal weight set is specified with a DEA model that intends to maximize the average efficiency. However, we will confront a non-linear fractional problem due to the existence of the average sum of efficiency scores in the objective function. Hence, an alternative method is proposed to model employee efficiency utilizing an aggregated virtual unit. The inputs and outputs for this aggregated unit are the summations of inputs and outputs of distinct operations, respectively, for which the employee has worked. Therefore, Eq. (3) is used to represent employee efficiency.

$$E^{ep} = \frac{\sum_{r=1}^{s}\sum_{j=1}^{n}\alpha_j^{ep}u_r^{ep}Y_{rj}}{\sum_{i=1}^{m}\sum_{j=1}^{n}\alpha_j^{ep}v_i^{ep}X_{ij}} \tag{3}$$

Therefore, the model to find the best score of average efficiency for each employee *e* of position *p* is given below:

$$E^{ep} = \max \frac{\sum_{r=1}^{s}\sum_{j=1}^{n}\alpha_j^{ep}u_rY_{rj}}{\sum_{i=1}^{m}\sum_{j=1}^{n}\alpha_j^{ep}v_iX_{ij}}$$

(optimization for each employee *e* in each position *p*)
s.t.

$$\frac{\sum_{r=1}^{s}u_rY_{rj}}{\sum_{i=1}^{m}v_iX_{ij}} \le 1, \qquad j = 1,\dots,n \tag{4}$$

$$v_i, u_r \ge 0, \qquad i = 1,\dots,m, \quad r = 1,\dots,s$$

Using the modifications proposed by Charnes and Cooper [18], we can rewrite Model (4) into the following LP model.

$$E^{ep} = \max \sum_{r=1}^{s}\sum_{j=1}^{n}\alpha_j^{ep}u_rY_{rj}$$

(optimization for each employee *e* in each position *p*)
s.t.

$$\sum_{i=1}^{m}\sum_{j=1}^{n}\alpha_j^{ep}v_iX_{ij} = 1, \tag{5}$$

$$\sum_{r=1}^{s}u_rY_{rj} - \sum_{i=1}^{m}v_iX_{ij} \le 0, \qquad j = 1,\dots,n$$

$$v_i, u_r \ge 0, \qquad i = 1,\dots,m, \quad r = 1,\dots,s$$

Obtaining the optimal values of v_i and u_r in Model (5) and denoting them by *ep* and $*$, the average efficiency of each employee can be calculated as follows:

$$E^{ep*} = \sum_{r=1}^{s}\sum_{j=1}^{n}\alpha_j^{ep}u_r^{ep*}Y_{rj} \tag{6}$$

Thus, as the employee efficiency comes to its optimal level, the efficiencies of distinct operation DMUs in which employee *ep* has worked are measured below:

$$E_j^{ep*} = \frac{\sum_{r=1}^{s} u_r^{ep*} Y_{rj}}{\sum_{i=1}^{m} v_i^{ep*} X_{ij}} \tag{7}$$

To measure teammate-adjusted efficiencies, we need to obtain the efficiencies related to two-person combinations of employees working in distinct operations, as shown in Model (8).

$$E^t = \max \sum_{r=1}^{s} \sum_{j=1}^{n} \alpha_j^t u_r Y_{rj}$$

(optimization for each two-person combination t)
s.t.

$$\begin{aligned} & \sum_{i=1}^{m} \sum_{j=1}^{n} \alpha_j^t v_i X_{ij} = 1, & & \\ & \sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \le 0, & & j = 1,\ldots,n \\ & v_i, u_r \ge 0, & & i = 1,\ldots,m, \quad r = 1,\ldots,s \end{aligned} \tag{8}$$

where α_j^t is a binary matrix representing the presence of two-person combination t in distinct operation DMU j. This LP optimization model is run for two-person combinations of employees, $t = 1,\ldots,T$. The maximum number of these combinations is obtained from the selection of two persons from total employees minus the combinations of two employees working in the same position. Thus, $T \le \binom{\sum_{p=1}^{K} H_p}{2} - \sum_{p=1}^{K} \binom{H_p}{2}$, where $\sum_{p=1}^{K} H_p$ is the total number of employees in different positions and $\binom{H_p}{2}$ is the number of 2-combinations within the set of all employees in the same position p.

At the end of Step 1, we also need to measure the efficiencies of a whole group of employees working in distinct operations, as shown in Model (9)
.

$$E^g = \max \sum_{r=1}^{s} \sum_{j=1}^{n} \alpha_j^g u_r Y_{rj}$$

(optimization for each group g)
s.t.

$$\begin{aligned} & \sum_{i=1}^{m} \sum_{j=1}^{n} \alpha_j^g v_i X_{ij} = 1, & & \\ & \sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \le 0, & & j = 1,\ldots,n \\ & v_i, u_r \ge 0, & & i = 1,\ldots,m, \quad r = 1,\ldots,s \end{aligned} \tag{9}$$

where α_j^g is a binary matrix representing the presence of group g in distinct operation DMU j. This LP optimization model is run for different groups of employees, $g = 1,\ldots,G$. The maximum number of these groups is obtained through selection of an employee from each position. Thus, $G \le \prod_{p=1}^{K} H_p$ where H_p is the number of employees working in position p.

2.2. Step 2

At Step 1, the efficiencies are measured from three perspectives. (1) Individual employees, (2) two-person combinations of employees, and (3) whole group of employees. In Step 2, the efficiency of employees is adjusted according to their teammates' relative level of performance.

In this regard, we first define the efficiency ratio of teammates to the employee under evaluation. Such an efficiency ratio has two implications: (a) The higher efficiency of a teammate in operations in which the employee under evaluation is not present indicates the higher relative performance of the teammate; (b) The higher efficiency of an employee under evaluation in operations in which a teammate is not present indicates the lower relative performance of the teammate. Thus, we define the efficiency ratio of teammates against the employee under evaluation as follows.

Definition 2 The efficiency ratio of teammates against the employee under evaluation is

$$R_{\substack{ep \\ p \neq p'}}^{e'p'} = \begin{cases} \dfrac{\underset{j=1,\dots,n}{Average}\, \gamma_{ep,j}^{e'p'} E_j^{e'p'}}{\underset{j=1,\dots,n}{Average}\, \gamma_{e'p',j}^{ep} E_j^{ep}} & \{\gamma_{t,j}^{ep}\}, \{\gamma_{t,j}^{e'p'}\} \neq \varnothing, \\ \dfrac{E^{t=\{ep,e'p'\}}}{\underset{j=1,\dots,n}{Average}\, \gamma_{e'p',j}^{ep} E_j^{ep}} & \{\gamma_{t,j}^{ep}\} \neq \varnothing, \{\gamma_{t,j}^{e'p'}\} = \varnothing, \\ \dfrac{\underset{j=1,\dots,n}{Average}\, \gamma_{ep,j}^{e'p'} E_j^{e'p'}}{E^{t=\{ep,e'p'\}}} & \{\gamma_{t,j}^{ep}\} = \varnothing, \{\gamma_{t,j}^{e'p'}\} \neq \varnothing, \\ 1 & \{\gamma_{t,j}^{ep}\}, \{\gamma_{t,j}^{e'p'}\} = \varnothing. \end{cases} \tag{10}$$

where $E_j^{e'p'}$ is obtained through Eq. (7) and $E^{t=\{ep,e'p'\}}$ through Model (8). Moreover, $\gamma_{ep,j}^{e'p'}$ is a binary matrix representing the presence of teammate e' of position p' in DMU j, while the employee e of position p is not present in the same operation of DMU j. Likewise, $\gamma_{e'p',j}^{ep}$ is a binary matrix representing the presence of employee e of position p in DMU j, while his/her teammate employee e' of position p' is not present in the same operation of DMU j. The first item of Eq. (10) is related to a case in which $\{\gamma_{t,j}^{ep}\}, \{\gamma_{t,j}^{e'p'}\} \neq \varnothing$, which means that both counter-presences of the employee under evaluation and his/her teammates are applicable. Otherwise, as expressed in the second, third, and fourth items of Eq. (10), in the case that either $\{\gamma_{t,j}^{ep}\}$ or $\{\gamma_{t,j}^{e'p'}\}$ does not exist, we replace it with the efficiency of the two-person combination, $E^{t=\{ep,e'p'\}}$. In doing so, on the one hand, we utilize the most available data (for instance $\underset{j=1,\dots,n}{Average}\, \gamma_{e'p',j}^{ep} E_j^{ep}$ in the second item) to estimate the relative performance of the employee under evaluation against his/her teammates and, on the other hand, we use $E^{t=\{ep,e'p'\}}$ as a neutral value to make the obtained efficiency ratio comparable with other equivalent values of $R_{\substack{ep \\ p \neq p'}}^{e'p'}$. It is clear that an employee is not the teammate of himself or herself, thus $R_{\substack{ep \\ p = p'}}^{e'p'} = 0$

To calculate the teammate-adjusted efficiencies, we consider an input-output model. We have K inputs related to the efficiency ratio of teammates to the employee under evaluation and one output related to the efficiency of the associated group. A simplified method for this problem is weighting the inputs and output by pre-determined fixed weights. In contrast, DEA provides weights that are obtained directly from the data and several prior assumptions related to fixed weights are avoided. Besides, the weights are determined in a way that finds the optimal set of weights. Therefore, we construct another DEA model with the efficiency ratio of teammates to the employee under evaluation; thus, $R_{ep}^{e'p' \in g}$ represents K inputs and the efficiency of the associated group; E^{g*} represents one output, as presented in Model (11), to measure the adjusted employee efficiencies E_{adj}^{ep}.

$$E_{adj}^{ep} = \max \sum_{g=1}^{G} \beta_g^{ep} \hat{u} E^{g*}$$

(optimization for each employee e in position p)
s.t.

$$\sum_{p'=1}^{K}\sum_{g=1}^{G} \beta_g^{ep} \hat{v}_{p'} R_{ep}^{e'p'\in g} = 1, \qquad (11)$$

$$\beta_g^{\bar{e}\bar{p}} \hat{u} E^{g} - \sum_{p'=1}^{K} \beta_g^{\bar{e}\bar{p}} \hat{v}_{p'} R_{\bar{e}\bar{p}}^{e'p'\in g} \le 0, \qquad \bar{p} = 1,\dots,K \;,\quad \bar{e} = 1,\dots,H_{\bar{p}} \;,\quad g = 1,\dots,G$$

$$\hat{v}_p, \hat{u} \ge 0, \qquad p = 1,\dots,K$$

where $\hat{v}_p$ and $\hat{u}$ are the multiplier variables of input p and the single output, respectively. Besides, β_g^{ep} is a binary matrix representing the presence of employee e of position p in group g.

3. Application to Oil and Gas Wells Drilling

Various operations have the structure of multiple positions with rotational employees, as shown in Fig. 1. To illustrate the capabilities of the proposed model in a real situation, an application to oil and gas wells drilling is discussed. The case study is based on the data of 20 wells drilled in the South Pars gas field from the year 2011 to 2015. South Pars/North Dome field with the ownership shared between Iran and Qatar is by far the world's largest natural gas field located in the Persian Gulf. We employ the methodology presented in Section 2 to evaluate the performance of 39 employees in four positions who have worked in three projects of phases 16, 17B, and 18B, which consist of 160 distinct operations.

3.1. Inputs and output

According to the drilling programs developed by drilling engineers in the South Pars gas field, the drilling operation of a well in this field starts with drilling a 32" diameter hole and it continues with drilling holes with 24", 16", 12 ¼", and 8 ½" diameters. The scope of the present DEA application is the 12 ¼" hole section. The operation of the first drilling bit in the 12 ¼" section starts approximately from 1600m depth and lasts approximately 1200 meters until reaching 2800m depth. The length of the whole wells in the South Pars gas field is around 4000 meters. To fairly reflect the drilling performances, the factors influencing the difficulty level of a directional well have been included in the inputs. The inverse directional drilling index (X_1), Non-sliding hours (X_2), formation's softness (X_3), bit's life (X_4), and expected learning achieved (X_5) are the input variables of the model. The Directional Drilling Index (DDI), proposed by Oag and Williams [19], is a technical measure of a well's difficulty and the percentage of non-sliding hours is specified based on rotating and sliding hours and softness of the formation is a quantified value between 0 and 4 based on the lithology and hardness data extracted from daily geology reports. Bit's life is another input to the model and is a quantified value between 0 and 16. When a bit is pulled out of the hole after drilling, the condition of the bit is recorded using a standard system of letters and numbers called dull grading recognized by the International Association of Drilling Contractors (IADC). A grading scale between 0-8 is used to note the amount of wear on the inner and outer rows of a bit. Therefore, the sum of the inner and outer wears and the bit's life, which is the opposite, ranges between 0-16. Calculation of the bit's life during the drilling operation is supported by the concept of Mechanical Specific Energy (MSE), as discussed by Abbas [20], Liu et al. [21], and Abbas et al. [22]. The last input, which is the expected learning achieved, will be discussed in the next section.

Time-related costs of a drilling operation are high, up to $150,000 a day, on an offshore jack-up rig in the years from 2011 to 2015. In general, to drill faster, the weight On Bit (WOB) and the Revolutions Per Minute (RPM) can be increased. Increasing both of these parameters or either also increases the rate of wear. So, it is critical to find the optimum set of drilling parameters to achieve the desired rate of penetration [23]. Therefore, the output variable is the Rate of Penetration (ROP), in meters per hour, which is the speed at which the bit drills. Fig. 2 illustrates the structure of the DMUs constructed by four positions (drilling supervisors and directional drillers of the shifts day and night) that affect ROP as the output of drilling operations in the case of having five selected inputs.

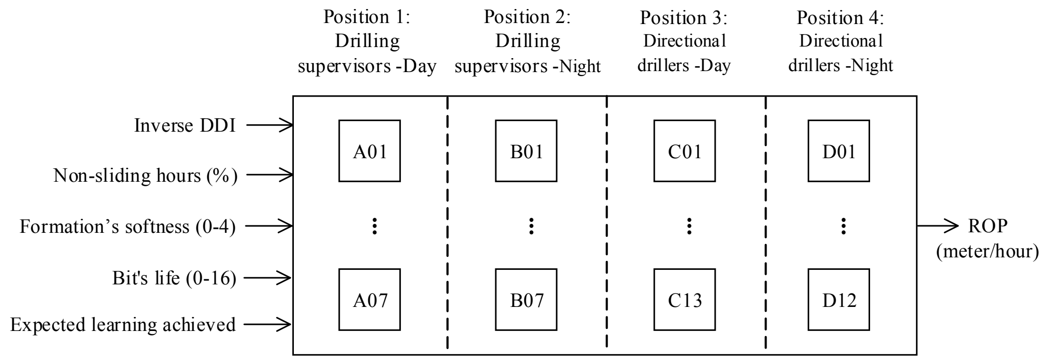

Fig. 2. Structure of a DMU constructed by four positions working in drilling projects

Table 1 shows the descriptive statistics of inputs and outputs for 160 distinct operations of 20 wells in the South Pars gas field, Phases 16, 17B, and 18B.

Tab. 1. Descriptive statistics of inputs and output in Step 1 in south pars gas field, phases 16, 17B, and 18B

Type	Variable	Mean	Minimum	Maximum	Std. dev.
Input	Inverse DDI	13.882	0.696	77.534	15.692
	Non-sliding hours (%)	84%	39%	100%	17%
	Formation’s softness (0-4)	2.298	0.135	3.673	0.746
	Bit's life (0-16)	14.409	10.247	16.000	1.322
	Expected learning achieved	0.476	0.095	0.727	0.163
Output	ROP (meter/hour)	10.498	3.433	23.944	3.587

The details of the data gathering process are laid out in the following. The Directional Drilling Index (DDI) is calculated by multiplying Measured Depth (MD), along Hole Displacement (AHD), and tortuosity, divided by True Vertical Depth (TVD). These data are obtained from directional survey reports containing the inclination and azimuth data. To ensure a desirable variable, the inverse of DDI has been used as the first input. The drilling time is divided into rotating and sliding hours. The next desirable input is the rotating or non-sliding hours, which is specified by the percentage of the total drilling time. Formation’s hardness is classified into different levels of soft, soft to medium-hard, medium-hard, and medium-hard to hard. Besides, the formation’s lithology affects the difficulty of drilling. For instance, the lithology types of Limestone, Calcareous Dolomite, Dolomitic Limestone, Dolomite, Argillaceous Limestone, Anhydrite, Claystone, Marl, and Shale have different difficulty levels that could be quantified based on the geologists’ judgment. To quantify the formation’s softness, a number has been assigned to each hardness level and each lithology. In doing so, we have a number between 0 and 4 based on the proportion of each hardness or lithology type within each formation. This forms the formation’s softness as the last input of the model. The ROP data are obtained from the daily mud logging reports. Mechanical Specific Energy (MSE) is also calculated using ROP, WOB, RPM, and Torque data in daily mud logging reports. Besides, the bit’s dull grading at the end of the bit’s operation is available in daily drilling reports. The dull grading level during the operation is estimated using the cumulative MSE. The bit’s life level is then calculated by subtracting the bit’s dull grading from 16, which is the life level of a new bit.

3.2. Expected learning achieved

The more drilling operations conducted, the more lessons learned obtained from successes and failures. This is a kind of intangible resource for the operational teams. Thus, we can consider the achieved learning as an input to our DEA model. This way, the operational teams will be fairly evaluated regarding the number of available lessons learned from past operations. To calculate the expected learning achieved, the concept of learning curves is deployed. Exponential models are utilized to construct the learning curves in case of an increase in output or productivity [9,10,24]. The two-parameter exponential model of Mazur and Hastie [25] is formulated as follows:

$$y = k\left(1 - e^{-(t/R)}\right) \tag{12}$$

where y represents the number of units produced since the start of production, t is the time that has elapsed since the start of production, k is the prediction of maximum performance after an infinite amount of time ($k \geq 0$), and R is the learning rate parameter which measures how fast an individual learns.

As explained about the case study, we confront 160 operations of 20 wells in three projects. However, there exist two breaks between these three projects. Thus, we need to adjust the expected learning achieved due to these two breaks. To assess the impact of an operation break, it is first necessary to quantify how much learning has been achieved prior to the break and then, quantify how much of that learning has been lost due to the break.

We divide the learning lost due to operation break into five categories, as given in Table 2. This is the same as the categories presented by Mislick and Nussbaum [13]. The weights in calculating Lost Learning Factor (LLF) and the percentage of learning lost in two breaks are also presented in Table 2. We will ultimately calculate LLF, which is the total percentage of learning that we have forgotten or lost.

Tab. 2. Lost learning factor (LLF) calculations for the case study

Factors	Remark related to the case study	Weight	Percent Learning Lost	
			Break 1	Break 2
Key personnel	drilling supervisors and directional drillers	25%	100%	100%
Supervisors	drilling operations manager and project manager	10%	100%	0%
Continuity of operation	nature of operation related to the section 12 ¼”	30%	0%	0%
Methods	drilling programs and lessons learned	20%	0%	0%
Key tools	drilling rig	15%	0%	100%
		LLF=	35%	40%

The weights imply the importance of each category and are estimated by the management team. In break one, which occurs before the start of project B, key personnel (drilling supervisors and directional drillers) and supervisors (drilling operations manager and project manager) have changed entirely. Thus, the percentages of learning lost regarding these two factors are 100%. However, the other factors including continuity of operation (hole section 12 ¼”), methods (drilling programs and available lessons learned), and key tools (drilling rig) remained the same as those in the project A. In break two, which occurred before the start of the project C, key personnel (drilling supervisors and directional drillers) changed entirely and the project utilized another drilling rig. Therefore, the percentages of the learning lost regarding these two factors are 100% and the other factors have remained the same as those in the project B. Applying weighted average in the breaks one and two results in LLF=35% and 40%, respectively.

As a rule of thumb, we set k=1 and R=10 in Eq. (12) to construct a learning curve that is suitable for representing the learning expectations in the scope of 20 wells as the operation sequences. Thus, $L_c = 1 - e^{-(c/10)}$, where L_c is the expected learning achieved in the operation sequence c. Fig. 3 shows the learning curves constructed over 160 operation DMUs related to 20 wells in three projects. It also presents learning lost after two breaks in the drilling operation that result in modified learning curves.

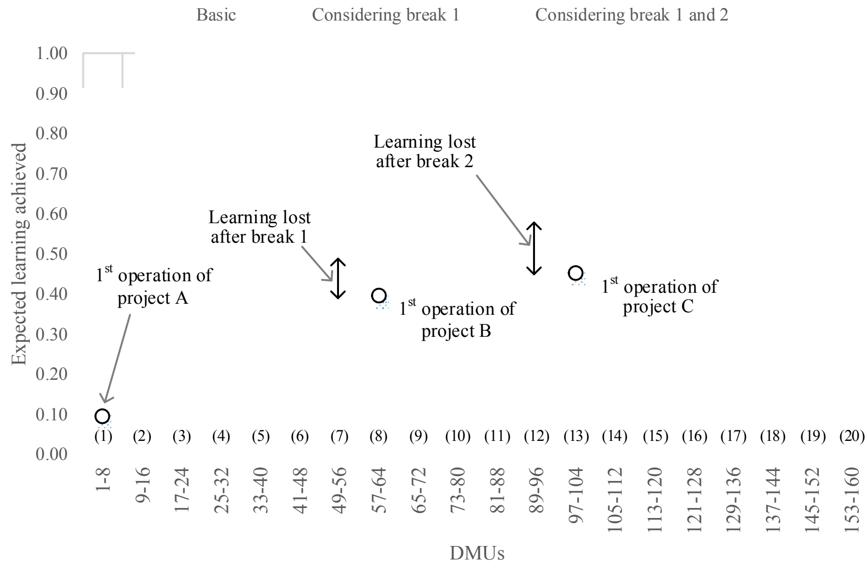

Fig. 3. Expected learning achieved for 160 operations of 20 wells in three projects

Table 3 shows the parameters required for calculating the expected learning achieved for the mentioned two breaks.

Tab. 3. Parameters of expected learning achieved for two breaks in operation

Break	Learning achieved before break	LLF	Learning lost	original L for the first operation after break	revised L for the first operation after break	Operation number on the original learning curve
1	0.41	35%	0.14	0.55	0.41	$5.2 \simeq 5$
2	0.50	40%	0.20	0.63	0.43	$5.7 \simeq 6$

* L is the expected learning achieved, which is depicted in Fig. 3.

As shown in Table 3, the learning achieved before break one is $L_7 - L_1 = 0.41$. By applying LLF of 35% to the learning achieved, the learning lost is obtained as $0.41 \times 35\% = 0.14$. The first operation after break one, L_8, is estimated by the original value of L_8 in the basic learning curve, which is 0.55 minus the amount of learning lost, 0.14. Thus, $L_8 = 0.55 - 0.14 = 0.41$. Finally, we need to find the operation sequence on the original learning curve, which is approximately the same as the estimated L of the first operation after the break. From the basic learning curve equation, we have $e^{-(c/10)} = 1 - L_c$. Then, $c = -10\ln(1 - L_c)$. Therefore, the operation number on the original learning curve which is approximately the same as $L_8 = 0.41$ is $c = 5.2 \simeq 5$. The first operation of the project B is shown appropriately in Fig. 3. Likewise, the operation number on the original learning curve which is approximately the same as $L_{13} = 0.43$ is $c = 5.7 \simeq 6$. Eventually, according to the constructed learning curve, we obtain the expected learning achieved as an input, as presented in Table 3.

3.3. Employees and their presence in operations

As discussed in the proposed model, we need α_j^{ep} in Model (5), α_j^t in Model (8), α_j^g in Model (9), $\gamma_{ep,j}^{e'p'}$ in Eq. (10), and β_g^{ep} in Model (11). All of these binary matrixes representing the presence of employee *ep*, two-person combination *t*, or group *g* in distinct operation DMU *j*, directly or indirectly, can be extracted from Table 4.

Tab. 4. Presence of employees in distinct operation DMUs

Position	Employee	DMUs																												
		j1-8	j9-16	j17-21	j22-24	j25-32	j33-35	j36-40	j41-48	j49-56	j57-64	j65-67	j68-72	j73-77	j78-80	j81-83	j84-88	j89-93	j94-96	j97-103	j104	j105-108	j109-111	j112	j113-117	j118-120	j121-126	j127-128	j129-136	j137-144	j145-152	j153-160
Drilling supervisors -Day	A01		1	1		1	1	1		1																						
	A02																			1			1	1			1	1			1	
	A03	1			1																											
	A04								1																							
	A05																				1	1			1	1			1	1		1
	A06										1				1	1	1															
	A07											1	1	1				1	1													
Drilling supervisors -Night	B01																						1	1	1	1			1	1		1
	B02																			1	1	1					1	1			1	
	B03										1			1			1	1	1													
	B04											1	1		1	1																
	B05	1	1	1	1	1		1		1																						
	B06						1																									
	B07								1																							
Directional drillers -Day	C01	1		1	1		1	1																								
	C02		1						1																							
	C03					1				1																						
	C04										1	1							1													
	C05												1	1	1	1																
	C06																1			1	1											
	C07																	1													1	
	C08																						1	1								
	C09																					1										
	C10																								1	1						
	C11																											1	1			
	C12																										1					1
	C13																													1		
Directional drillers -Night	D01	1				1	1			1																						
	D02		1						1																							
	D03			1	1			1																								
	D04										1																					
	D05											1	1	1	1																	
	D06															1	1	1	1			1	1									1
	D07																			1	1											
	D08																							1	1						1	
	D09																									1						
	D10																										1	1				
	D11																												1			
	D12																													1		

3.4. Results

In Step 1, Models (5), (8), and (9) are applied to the collected dataset of 160 distinct operations. Table 5 presents descriptive statistics of the efficiencies related to 39 employees, 118 two-person combinations, and 29 groups that have worked in 160 distinct operation DMUs. Due to space limitations, results of E_j^{ep}, E_j^{t}, and E_j^{g} are not presented in the paper.

In order to clarify the results, we present those related to the first employee A01. Table 6 shows the efficiency scores of two-person combinations related to employee A01 based on Model (8). Besides, employee A01, as a drilling supervisor of day, has worked in four different groups, as stated in Table 7. The efficiencies of the related groups, E^g, are also presented in Table 7. For instance, it shows that employee A01 has his best performance in the team {A01B05C01D03} with teammates B05, C01, and D03. Moreover, Table 7 shows the efficiency ratio of teammates, $R_{ep}^{e'p'}$, related to employee A01.

Tab. 5. Descriptive statistics of efficiencies related to employees, two-person combinations, and groups

Variable	Count	Mean	Minimum	Maximum	Std. dev.
E^{ep}, efficiency score of employees	39	0.546	0.380	0.814	0.092
E^{t}, efficiency score of two-person combinations	118	0.564	0.290	0.913	0.116
E^{g}, efficiency score of groups	29	0.589	0.290	0.913	0.140

Tab. 6. Efficiency scores of two-person combinations related to employee A01

Two-person combination	$E^{t=\{ep,e'p'\}}$
{A01,B05}	0.547
{A01,B06}	0.517
{A01,C01}	0.607
{A01,C02}	0.580
{A01,C03}	0.514
{A01,D03}	0.640
{A01,D02}	0.580
{A01,D01}	0.510

Tab. 7. Efficiency ratio of teammates related to employee A01

Employee in groups	E^{g}	$\underset{j=1,\ldots,n}{Average}\ \gamma_{e'p',j}^{ep}E_j^{ep}$			$\underset{j=1,\ldots,n}{Average}\ \gamma_{ep,j}^{e'p'}E_j^{e'p'}$			$R_{ep}^{e'p'}$		
		B	C	D	B	C	D	B	C	D
A01 {A01B05C01D03}	0.640	0.500	0.538	0.533	0.738	0.770	0.781	1.477	1.432	1.465
A01 {A01B05C02D02}	0.580	0.500	0.565	0.565	0.738	0.369	0.369	1.477	0.653	0.653
A01 {A01B05C03D01}	0.514	0.500	0.600	0.617	0.738	NA	0.822	1.477	0.857	1.333
A01 {A01B06C01D01}	0.517	0.572	0.538	0.617	NA	0.770	0.822	0.904	1.432	1.333

Teammates B, C, and D are drilling supervisor -night, directional driller -day, and directional driller -night, respectively.

According to Eq. (10), in order to calculate $R_{ep}^{e'p'}$, we need $\underset{j=1,\ldots,n}{Average}\ \gamma_{e'p',j}^{ep}E_j^{ep}$ and $\underset{j=1,\ldots,n}{Average}\ \gamma_{ep,j}^{e'p'}E_j^{e'p'}$, as shown in Table 7. Let us examine the efficiency ratio of teammate B05 against employee A01, which is $R_{\text{A01}}^{\text{B05}}$. From the results of Step 1 and the presence data of Table 4, we calculate $\underset{j=1,\ldots,n}{Average}\ \gamma_{\text{B05},j}^{\text{A01}}E_j^{\text{A01}}$ =0.5 and $\underset{j=1,\ldots,n}{Average}\ \gamma_{\text{A01},j}^{\text{B05}}E_j^{\text{B05}}$ =0.738. Thus, $R_{\text{A01}}^{\text{B05}}$ = 0.738/0.5 = 1.477.

As seen in Table 4, there is no operation in which "employee C03 is present; however, A01 is not". The term NA in Table 7 indicates these situations. In this regard, let us examine the efficiency ratio of teammate C03 against employee A01, which is $R_{\text{A01}}^{\text{C03}}$. From the results of Step 1 and the present data of Table 4, we calculate $\underset{j=1,\ldots,n}{Average}\ \gamma_{\text{C03},j}^{\text{A01}}E_j^{\text{A01}}$=0.6 and we see that $\underset{j=1,\ldots,n}{Average}\ \gamma_{\text{A01},j}^{\text{C03}}E_j^{\text{C03}}$ is not available. From Table 6, we know that $E^{t=\{\text{A01,C03}\}}$ =0.514. Thus, according to the second item of Eq. (10), $R_{\text{A01}}^{\text{C03}}$= 0.514/0.6 = 0.857.

In Step 2 aimed at measuring teammate-adjusted efficiencies, we have four inputs and one output. For employee A01, model (11) is run four times due to the presence of A01 in four groups. The inputs and outputs are shown in the columns related to $R_{ep}^{e'p'}$ and E^{g} in Table 7, respectively.

Table 8 presents descriptive statistics for all 39 employees in their presence in 116 groups and

Table 9 compares basic and teammate-adjusted efficiency scores of employees obtained by Models (5) and (11), respectively.

Tab. 8. Descriptive statistics for inputs and output of Step 2 related to the presence of 116 employees in groups

Type	Variable	Mean	Minimum	Maximum	Std. dev.
Inputs, $R_{ep}^{e'p'}$	Drilling supervisors -Day	0.999	0.664	1.532	0.224
	Drilling supervisors -Night	1.025	0.515	2.139	0.302
	Directional drillers -Day	1.073	0.467	1.940	0.289
	Directional drillers -Night	1.032	0.593	1.566	0.229
Output, E^g	Efficiency score of the related group	0.589	0.290	0.913	0.140

Tab. 9. Efficiency scores of employees

Position	Employee	Efficiency	
		Basic, model (5)	Adjusted, model (11)
Drilling supervisors -Day	A01	0.543	0.455
	A02	0.506	0.479
	A03	0.814	0.957
	A04	0.380	0.311
	A05	0.473	0.502
	A06	0.572	0.532
	A07	0.630	0.685
Drilling supervisors -Night	B01	0.456	0.421
	B02	0.528	0.711
	B03	0.636	0.800
	B04	0.561	0.489
	B05	0.598	0.689
	B06	0.517	0.465
	B07	0.380	0.378
Directional drillers -Day	C01	0.686	0.847
	C02	0.459	0.525
	C03	0.514	0.505
	C04	0.530	0.590
	C05	0.625	0.842
	C06	0.619	0.910
	C07	0.569	0.776
	C08	0.551	0.725
	C09	0.541	0.711
	C10	0.563	0.898
	C11	0.457	0.516
	C12	0.472	0.526
	C13	0.428	0.450
Directional drillers -Night	D01	0.606	0.665
	D02	0.459	0.505
	D03	0.662	0.761
	D04	0.564	0.641
	D05	0.591	0.610
	D06	0.551	0.679
	D07	0.682	0.926
	D08	0.482	0.525
	D09	0.708	1.000
	D10	0.494	0.556
	D11	0.456	0.492
	D12	0.428	0.458

According to Table 9, the adjusted efficiency of employee A01 is 0.455, which is less than his basic efficiency of 0.543, because employee A01 has teammates B05, C01, D03, D01 that have a higher efficiency ratio $R_{ep}^{e'p'}$ against employee A01 in the associated groups, as shown in Table 7. This finding, as revealed by Model (11), is given in comparison to the efficiency ratios of other employees and their teammates.

Fig. 4 presents the ranking of employees in four positions.

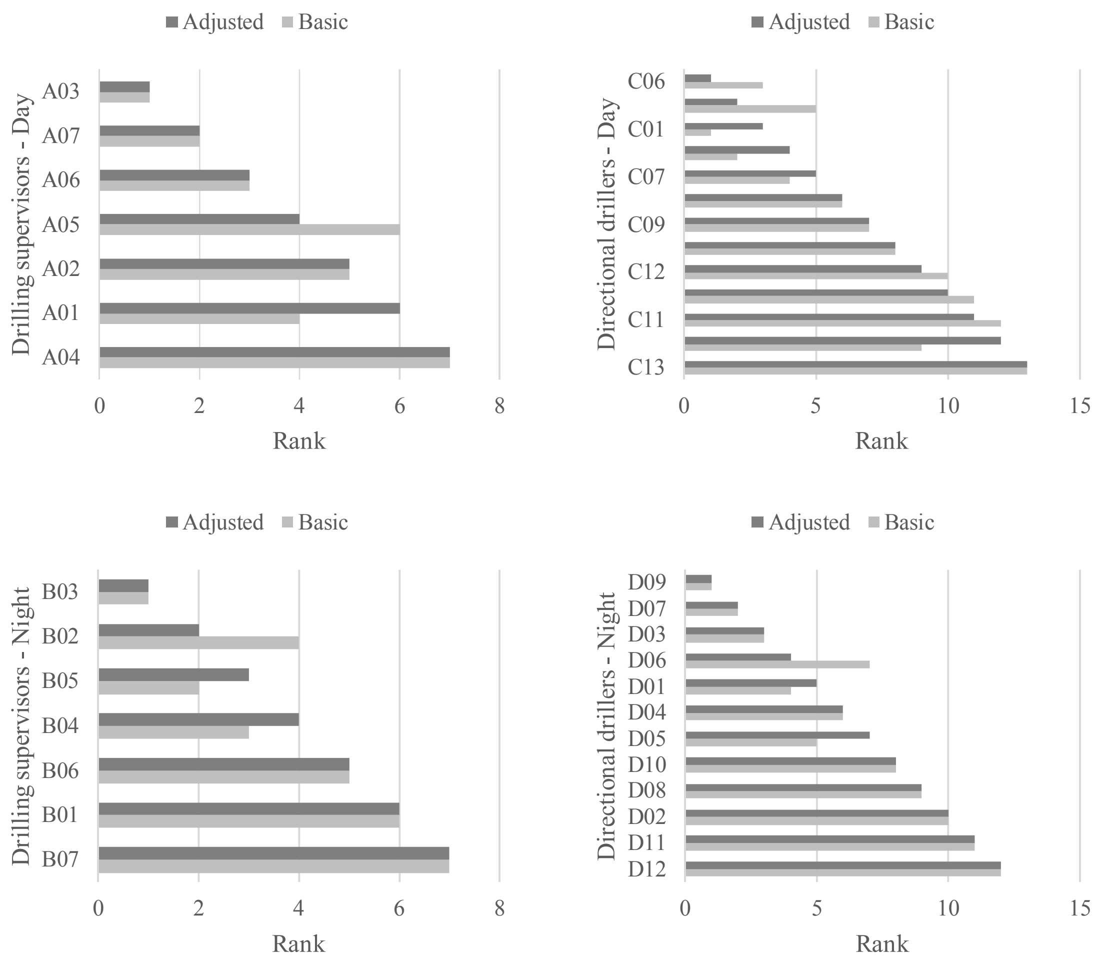

Fig. 4. Comparison of employee rankings based on basic and adjusted efficiencies

Although employee A01 has the 4th rank in the basic model, he has been demoted to the 6th rank after measuring adjusted efficiencies considering the relative performance of his teammates. In contrast, employee A05 has been promoted to the 4th rank considering teammate-adjusted efficiencies. Likewise, there are changes in the rankings of other employees in other positions, as shown in Fig. 4. Moreover, Model (11), which measures adjusted efficiencies, results in a wider range of efficiencies, which implies greater discrimination power of the proposed model, as shown in Fig. 5.

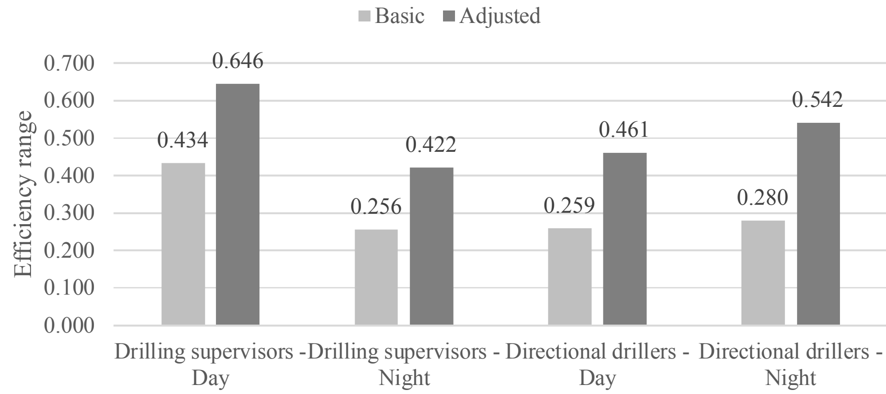

Fig. 5. Comparison of efficiency ranges between basic and adjusted models

While the minimum and maximum efficiencies of drilling supervisors of the day in the basic model are 0.380 and 0.814 according to Table 9, the minimum and maximum efficiency rates of this position in the adjusted model are 0.311 and 0.957. It is shown that the adjusted model better discriminates between the lowest and highest performances by a range of 0.957 - 0.311 = 0.646 against 0.814 - 0.380 = 0.434 in the basic model. Likewise, the ranges of efficiencies related to the other positions demonstrate greater discrimination power of the adjusted model, as shown in Fig. 5.

4. Conclusion

This paper addressed the following research questions: (a) how one should measure the teammate-adjusted efficiency of employees in a multi-position system? and (b) what are the ranks of the drilling supervisors and directional drillers in the drilling operations of 20 wells in the South Pars gas field considering teammates' performances and learning expectations?

This study attempted to answer the first research question by proposing a DEA model in the first step to measure the average efficiency of the individual, the two-person combination, and the whole group of employees in a multi-position system. The second step utilized another DEA model to measure the teammate-adjusted efficiency of employees. To achieve the aforementioned aim, we defined the efficiency ratio of teammates against the employees under evaluation. It helped us model two aspects: (a) The more efficiency of a teammate in operations, in which the employee under evaluation is not present, indicates the more relative performance of the teammate; (b) The higher efficiency of an employee under evaluation in operations in which a teammate is not present indicates the less relative performance of the teammate.

We also tried to answer the second question as follows. The inverse directional drilling index, non-sliding hours, formation's softness, bit's life, and the expected learning achieved were selected as inputs and ROP was chosen as output. Since the lessons learned as an intangible resource help the subsequent operational teams to tackle the operational problems more successfully, we considered the expected learning achieved as an input to the model. It was formulated by an exponential learning curve incorporating the effect of learning lost after two breaks in the operation. The proposed DEA model was then applied to perform an empirical study of 20 wells with 160 distinct operations in the South Pars gas field. The results revealed which employees were of high performance before and after adjusting efficiencies. Such adjusted scores provide the organization with an indicator for fairly ranking the employees as some of them demoted or promoted to new ranks after considering the effect of their teammates. Besides, the adjusted scores indicate larger ranges of efficiencies, implying the greater discrimination power of the proposed model. Moreover, since the present paper is the first application of DEA for measuring the drilling performance of oil and gas wells, it can be a starting point for further research in such an interesting and critical field.

Future research includes the application of the proposed model to a general network or dynamic structures [26–28]. Further study is also required for investigating suppliers' performance in case of joint operations. Moreover, as the current study focuses on the ROP as a single output, an investigation of sustainability [29] or considering undesirable outputs are other interesting further research directions.

Acknowledgments

The authors would like to thank Dana Energy Company for supporting the present research that is associated with the development projects of Phases 15&16 and 17B&18B in the South Pars gas field.

References

[1] Baker Hughes, International Rig Count, (2019).

[2] Duguay, A., Sridhar, B., Boisson, G., and Dolmetta, L., "Managing Shift Work in the Offshore Workplace", *Society of Petroleum Engineers*, (2012).

[3] Brun, A., Aerts, G., and Jerkø, M., "How to achieve 50 percent reduction in offshore drilling costs", *McKinsey*, (2015).

[4] Charnes, A., Cooper, W.W., and Rhodes, E., "Measuring the efficiency of decision making units", *European Journal of Operational Research*, Vol. 2, No. 6, (1978), pp. 429-444.

[5] Cook, W.D. and Seiford, L.M., "Data envelopment analysis (DEA) - Thirty years on", *European Journal of Operational Research*, Vol. 192, No. 1, (2009), pp. 1-17.

[6] Emrouznejad, A. and Yang, G., "DEA Bibliography of recent four decades (1978-2016)", Vol. 61, (2018), pp. 4-8.

[7] Aldamak, A. and Zolfaghari, S., "Review of efficiency ranking methods in data envelopment analysis", *Measurement*, Vol. 106, (2017), pp. 161-172.

[8] Jablonowski, C., Ettehadtavakkol, A., Ogunyomi, B., and Srour, I., "Integrating Learning Curves in Probabilistic Well-Construction Estimates", *SPE Drilling & Completion*, Vol. 26, No. 01, (2011), pp. 133-138.

[9] Glock, C.H., Grosse, E.H., Jaber, M.Y., and Smunt, T.L., "Applications of learning curves in production and operations management: A systematic literature review", *Computers & Industrial Engineering*, Vol. 131, (2019), pp. 422-441.

[10] Anzanello, M.J. and Fogliatto, F.S., "Learning curve models and applications: Literature review and research directions", *International Journal of Industrial Ergonomics*, Vol. 41, No. 5, (2011), pp. 573-583.

[11] Li, Y., Yang, X., and Yang, Z., "Uncertain learning curve and its application in scheduling", *Computers & Industrial Engineering*, Vol. 131, (2019), pp. 534-541.

[12] Wright, T.P., "Factors Affecting the Cost of Airplanes", *Journal of the Aeronautical Sciences*, Vol. 3, No. 4, (1936), pp. 122-128.

[13] Mislick, G.K. and Nussbaum, D.A., Chapter 12: Learning Curves, Production Breaks/Lost Learning, Wiley, (2015).

[14] Chang, D.-S., Liu, W., and Yeh, L.-T.T., "Incorporating the learning effect into data envelopment analysis to measure MSW recycling performance", *European Journal of Operational Research*, Vol. 229, No. 2, (2013), pp. 496-504.

[15] Lyu, K., Bian, Y., and Yu, A., "Environmental efficiency evaluation of industrial sector in China by incorporating learning effects", *Journal of Cleaner Production*, Vol. 172, (2018), pp. 2464-2474.

[16] Ang, S., Chen, M., and Yang, F., "Group cross-efficiency evaluation in data envelopment analysis: An application to Taiwan hotels", *Computers & Industrial Engineering*, Vol. 125, (2018), pp. 190-199.

[17] Sueyoshi, T., Yuan, Y., and Goto, M., "A literature study for DEA applied to energy and environment", *Energy Economics*, Vol. 62, (2017), pp. 104-124.

[18] Charnes, A. and Cooper, W.W., "Programming with linear fractional functionals", *Naval Research Logistics Quarterly*, Vol. 9, No. 3-4, (1962), pp. 181-186.

[19] Oag, A.W. and Williams, M., "The Directional Difficulty Index - A New Approach to Performance Benchmarking", *Society of Petroleum Engineers*, (2000).

[20] Abbas, R.K., "A review on the wear of oil drill bits (conventional and the state of the

art approaches for wear reduction and quantification)", *Engineering Failure Analysis*, Vol. 90, (2018), pp. 554-584.

[21] Liu, Y., Kibbey, J., Bai, Y., and Wu, X., "Real-Time Bit Wear Monitoring and Prediction Using Surface Mechanics Data Analytics: A Step Toward Digitization Through Agile Development", *Society of Petroleum Engineers*, (2018).

[22] Abbas, R.K., Hassanpour, A., Hare, C., and Ghadiri, M., "Instantaneous Monitoring of Drill Bit Wear and Specific Energy as a Criteria for the Appropriate Time for Pulling Out Worn Bits", *Society of Petroleum Engineers*, (2014).

[23] Devereux, S., Drilling technology in nontechnical language, PennWell Corp, (2012).

[24] Grosse, E.H., Glock, C.H., and Müller, S., "Production economics and the learning curve: A meta-analysis", *International Journal of Production Economics*, Vol. 170, (2015), pp. 401-412.

[25] Mazur, J.E. and Hastie, R., "Learning as accumulation: A reexamination of the learning curve", *Psychological Bulletin*, Vol. 85, No. 6, (1978), pp. 1256-1274.

[26] Hu, Z., Yan, S., Li, X., Yao, L., and Zhifeng, L., "Evaluating the oil production and wastewater treatment efficiency by an extended two-stage network structure model with feedback variables", *Journal of Environmental Management*, Vol. 251, (2019), pp. 1-8.

[27] Jahangoshai Rezaee, M., Moini, A., and Bakhshour, F., "An Integrated Approach for Measuring Performance of Network structure: Case study on power plants", *International Journal of Industrial Engineering & Production Research (IJIEPR)*, Vol. 26, No. 4, (2015), pp. 255-268.

[28] Azbari, M.E., Olfat, L., Amiri, M., and Soofi, J.B., "A Network Data Envelopment Analysis Model for Supply Chain Performance Evaluation: Real Case of Iranian Pharmaceutical Industry", *International Journal of Industrial Engineering & Production Research (IJIEPR)*, Vol. 25, No. 2, (2014), pp. 125-137.

[29] Noveiri, M. and Kordrostami, S., "Multi-Period Sustainability Performance in the Presence of Discrete and Bounded Measures", *International Journal of Industrial Engineering & Production Research (IJIEPR)*, Vol. 30, (2019), pp. 507-528.

Follow This Article at The Following Site:

Nedaei H, Jalali Naini S G, Makui A. A DEA approach to measure teammate-adjusted efficiencies incorporating learning expectations: An application to oil & gas wells drilling. IJIEPR. 2021; 32 (1) :47-64
URL: http://ijiepr.iust.ac.ir/article-1-1039-en.html