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Data Envelopment Analysis (DEA) for Improving Ergonomics and Workplace Performance

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Abstract

The purpose of the study was to develop a framework utilizing the Constant Returns to Scale (CCR) model of Data Envelopment Analysis (DEA) to evaluate the performance of workers and ergonomic risk and identify their postural models from efficient frontiers. Surface Electromyography (EMG) data and upper limb joint angle data were collected from volunteers (Decision-Making Units (DMUs) to carry out the DEA analysis. The data was collected for both maximum voluntary isometric contractions (MVC) and simple dynamic exercises. The DEA analysis was performed in several phases, including problem formulation and Single-Input-Multiple-Output (SIMO) model analysis. The study used muscle activation levels and upper limb joint angles to evaluate the ergonomic risks and performance of workers and identify role models for typical workers to follow. The study found that incorporating kinematics and EMG data into the DEA model's CCR framework identified efficient frontiers for workers who exhibit less muscle activation and use optimal arm angles while performing their work. The study also showed that workers can learn from their role models who exhibit efficient techniques, including the appropriate arm angle for performing a particular task, to improve their own efficiency. By following these superior work procedures, workers can increase their efficiency, reduce the risk of musculoskeletal problems, and enhance their output. The study concluded that the DEA framework utilizing the CCR model, combined with kinematics and EMG data, can assist in determining the performance of workers and best practices for workers to improve their performance and reduce ergonomic risk.

Keywords: Ergonomics, Data envelopment analysis, Decision-making unit, Muscle activations, Joint angles.

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1 | Introduction

Ergonomics is a methodology that involves creating workspaces, products, tools, and systems that meet the needs and capabilities of users while also taking into account their physical, biomechanical, and psychological abilities. When these factors are not considered, there is a risk of ergonomic hazards that can result in injuries for workers performing different tasks in their workplace. Data Envelopment Analysis (DEA) is a non-parametric linear programming technique used to compare the performance of Decision-Making Units (DMUs) that utilize various inputs to generate multiple outputs [1]. This approach was first introduced by Charnes et al. [1] in 1978, and the concept of Constant Returns to Scale (CRS) was introduced. The DEA model assesses the efficiency of each DMU by calculating a ratio of weighted outputs to weighted inputs. The weights are assigned in a way that maximizes the ratio while ensuring that the total weighted inputs do not exceed a specific level and the total weighted outputs meet a certain minimum level. DEA has various models available, such as the CCR [1], BCC [2], SBM [3], and FDH [2] models. The study utilized the CCR [1] model DEA approach to measure the efficiency and productivity of DMUs in simple exercise processes that involve multiple inputs and outputs. The framework incorporated both kinematics and Electromyography (EMG) data to provide a comprehensive and unbiased evaluation of worker performance. Kinematics data provided information on the worker's movement, while EMG data assessed muscle activity and fatigue. EMG stands for EMG, which refers to the electrical signals generated by muscle contractions controlled by the nervous system. These signals are indicative of the activity of a muscle motor unit. EMG is increasingly being utilized in various clinical settings, engineering applications, and research labs due to its ease of use, non-invasiveness, and safety for patients [4]. For accurate EMG data collection, it is crucial to prepare the skin properly and place the electrodes correctly. This involves cleaning the skin, removing any hair, and using alcohol wipes to eliminate any oil, dirt, or residue. Inadequate skin preparation can result in extremely noisy and erratic signals from the muscles.

Additionally, the placement of electrodes is crucial and varies depending on the muscle being targeted, with the ideal location being the belly of the muscle [5]. When conducting a between-subject analysis of EMG amplitude, it is essential to utilize post-processing techniques such as Maximal Voluntary Contraction (MVC) normalization [6]. This approach, which involves calculating the Root Mean Square (RMS) of the EMG recording, is the most commonly used method for analyzing EMG signals. It provides a standardized denominator for multiple data series, resulting in normalized data that facilitates comparisons between participants. By using this technique, researchers can ensure the validity of their findings and minimize any discrepancies in the data [7]. The results of MVC normalization are typically expressed as a percentage of MVC, which represents the maximum force that a muscle can produce during a voluntary contraction. The analysis of human movement through motion analysis is a vital tool that can uncover significant insights into the hidden patterns of motion characteristics and provide kinematic data. This technique has proven to be particularly valuable in diverse areas, including sports training [8] and industrial work measurement [9].

The study shows that the DEA approach is a valuable technique for evaluating the ergonomic risks and performance of workers, enabling the identification of effective and average personnel to enhance their abilities and improve postural stability and balance through the CCR model framework. In research, DEA was employed to assess EMG sensors for use in prosthetic hands and was successful in determining the most effective sensor. It supported the selection of the best sensor at the decision-making [10]. Researchers employed DEA to assess EMG-based human-machine interfaces, and they concluded that DEA was successful in determining the best interface for human-machine interaction [11]. DEA has gained prominence in the field of EMG due to its non-parametric evaluation of multiple DMUs. Recent studies demonstrate DEA's effectiveness in assessing various EMG-based approaches, identifying optimal techniques for feature extraction, and evaluating EMG sensors for applications like prosthetic hands [12]. The convex hulls generated by DEA offer insights into DMU efficiency and can pinpoint the root causes. This has implications for diverse industries, including manufacturing and healthcare [13], [14]. Additionally, DEA has been utilized to assess human-machine interfaces and form tolerances in manufacturing components. In terms of efficiency, research suggests that optimal arm posture and reduced muscle activation lead to quicker task completion and fewer errors, particularly in physically demanding professions. The link between arm angle, muscle activation, and task efficiency underscores the importance of ergonomic design and training for enhanced work performance and reduced risk of fatigue and injury [15]. Efficiency in work performance can be improved by utilizing a combination of less muscle activation and an optimal arm angle [16]. The arm's angle also influences the efficiency of the task. The arm should be near the body, and the elbow should be bent to around 90 degrees for maximum efficiency [17]. In another study, compared to a raised arm position and increased muscle activity, a more neutral arm posture and lower muscle activity led to better task performance and lessened muscle fatigue [17].

To assess performance in industrial settings and identify areas for improvement, this study developed a DEA technique capable of generating convex hulls from both efficient and inefficient frontiers that encompass all observed data points. The convex hulls produced by DEA have been the subject of several research studies [18]. Convexity of the efficient frontier may be utilized to determine the kind of production technology, as Li and Reeves [19] proved by proposing a scale for measuring it. Researchers created a trustworthy system for assessing form tolerances, namely the straightness and flatness of manufactured components. It was demonstrated that the convexity of the efficient frontier may be utilized to pinpoint the sources of inefficiency in DMUs by studying DMUs with more convex efficient frontiers as compared to those with less convex efficient frontiers [20]. The application of DEA to the creation of convex hulls for portfolio selection shows that the convex hulls produced by DEA may be utilized to assess the performance of a stock portfolio [21], [22]. Efficient DMUs are those that provide, and the remaining DMUs, represented within the convex hull [23], are positioned between the efficient and inefficient frontiers, indicating varying levels of performance and efficiency.

Additionally, benchmarking for occupational health and safety performance is crucial in industrial settings, as it enables the recognition of weaknesses and the development of improvement methods using DEA [24]. The potential implications of this study extend beyond a specific occupational setting, with the DEA approach serving as a powerful tool to assess ergonomic risks and improve worker performance. These findings suggest that the DEA approach can be leveraged to optimize worker abilities and, ultimately, promote workplace safety and productivity.

2 | Problem Statements and Methods

The DEA model is employed in this study to assess the relative efficiency of each subject's muscle movements across various dimensions, including energy consumption and force production. The primary objective of this research is to establish an innovative framework for evaluating the efficiency of muscle movements during different exercises (e.g., sweeping exercises). In our investigation, trial numbers are considered as inputs, and the two EMG values serve as outputs. Consequently, we formulate a Single-Input-Multiple-Output (SIMO) model from the CCR model. Each participant engaged in five exercise trials, with muscle energy utilization being a key metric. Efficiency is evaluated based on the SIMO model derived from the CCR model. Those participants exhibiting lower muscle activation across the trials are considered more efficient and are less prone to muscle injuries. This research contributes to advancing our understanding of muscle movement efficiency and its implications for injury prevention.

The study comprises three distinct stages. The first stage involves the development of a new framework employing the CCR model of DEA to evaluate the efficiency of a system or process, which involves problem formulation and SIMO model formation. During the second stage, EMG and kinematic data will be collected from human participants to evaluate the efficiency of their muscle movements and arm angles during various exercises.

EMG data were collected from the subjects while performing the simple dynamic exercises (e.g., sweeping) and isometric Maximum Voluntary Contraction (MVC) tests. MVC results, where the subject reached the maximum activation level in three trials, were used as a physiological reference point to normalize the EMG signals. Then, each EMG signal from dynamic exercises was expressed as a percentage of MVC (% MVC). Furthermore, upper limb joint angles were recorded using a Vicon motion capture system with 10 cameras (Vicon Motion Systems, Oxford, UK). In the final stage, the EMG and kinematic data collected in the second stage will be utilized in the framework developed during the first stage. The DEA analysis will be carried out using the trial number as input and EMG and kinematic data as both outputs to assess the efficiency of the muscle and arm movements during the exercises.

Fig. 1. Flowchart of methodology.

2.1 | CCR Model

The Charnes, Cooper, and Rhodes (CCR) model, also called the CRS model, is a linear programming technique that assesses the efficiency of DMUs like organizations, institutions, or companies. First introduced by Charnes, Cooper, and Rhodes in 1978, the CCR model is a non-parametric linear programming approach that measures efficiency [1]. DEA is a method used to determine the relative efficiency of DMUs while keeping either inputs or outputs constant. The CCR model is based on the concept of efficient frontiers, which is the best-performing DMU. There are two main models used in DEA: the input-oriented model and the output-oriented model. In the input-oriented model, the input variables are kept constant while the output variables are maximized [25]. In the output-oriented model, the output variables are kept constant while the input variables are minimized. According to research, individuals with the best arm angles and the least amount of muscle activity are more efficient. Therefore, to minimize our output, we will be using the input-oriented model for our analysis.

Assume that there are 'n' number of DMUs need to evaluate where each DMU consumes varying amounts of 'm' different inputs to produce 's' different outputs. If DMUj needs x_{ij} of input' i' to produce y_{rj} of output' r', where $x_{ij} > 0$ and $y_{rj} > 0$ and λ_i, λ_r are the multipliers of input and output weights. For a particular DMU, the ratio of any single virtual output to a single virtual input provides a measure of efficiency that is a function of the multipliers, where the Input-oriented model is

Objective function

$$\max z = \sum_{r=1}^{s} \mu_r y_{r0}. \tag{1}$$

Subject to

$$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \tag{2}$$

$$\sum_{i=1}^{m} v_i x_{i0} = 1, \tag{3}$$

$$\mu_r, v_i \geq 0. \tag{4}$$

2.2 | Data Collection

Due to the time-consuming nature, finding volunteers solely for research purposes proved challenging. Consequently, a cohort of ten participants was recruited for data collection. This subject group, including 5 males and 5 females with an average height of 166.65±8.35 cm, an average weight of 72.4±25.28 kg, and an average age of 25.5±4.8 years, were recruited from the local university community, following the Institutional

Review Board (IRB) guidelines. For the recruitment procedure, flyers were distributed, and interested individuals were invited. A health survey was conducted on each participant to ensure there were no musculoskeletal issues that could impede their performance during the experiment. Informed consent was obtained from all participants prior to beginning the study after being informed about the potential risks and benefits. The subjects performed stretching exercises to warm up before the experiment, and alcohol wipes containing 62% Ethyl alcohol were used to sanitize the skin in the contact area of the EMG sensors, followed by hair removal using a disposable razor. Each subject wore four EMG sensors placed on the Flexor Carpi Radialis (FCR) and Biceps Brachii (BB) muscles connected to the Delsys Trigno Wireless system (Delsys Inc., Boston, MA, USA). The EMG sensors are composed of 99.9% silver, with each sensor measuring 27 mm x 37 mm x 15 mm with an interelectrode distance of 10 mm. Data collection is conducted at a sampling frequency of 1926 Hz, with a gain setting of 1000, a common-mode rejection ratio greater than 80 dB, and an input impedance exceeding 10^{15} **Ω**. A Butterworth band-pass filter ranging from 20 to 450 Hz was employed to filter the EMG data digitally. The quality of the EMG signal was monitored using EMG Works™, following the manufacturer's recommended criteria, which include a baseline noise < 15 μVrms, signal-to-noise ratio > 1.2, and line interference < 2. EMG sensors were attached to the BB and FCR muscles according to SENIAM recommendations shown in *Fig. 2.c* [26]. Subjects were instructed to perform a forearm exercise to activate the BB muscle group, and a Velcro-resistant band was used to immobilize the forearm of the subject at an elbow joint angle of 90 in a seated position shown in *Fig. 2.a* [27]. Additionally, subjects were instructed to perform a wrist exercise to activate the FCR muscle group. A Velcro-resistant band was utilized to maintain the wrist in a neutral position while the subject applied force in the direction indicated by the arrow in *Fig. 2.b* [28]. EMG data were collected from both BB and FCR muscles by using Delsys EMG Works™ (Version 4.8.0). To normalize the EMG signals, each subject performed three MVCs of their muscles without joint movement. 1-min of rest was provided between MVC movements for muscle regeneration. Each MVC movement was performed for around 5 seconds. For each muscle group, the highest MVC value was picked from the trials and then used as a physiological reference point to express the muscle activation of dynamic trials as a percentage of MVC to normalize the data as follows [29].

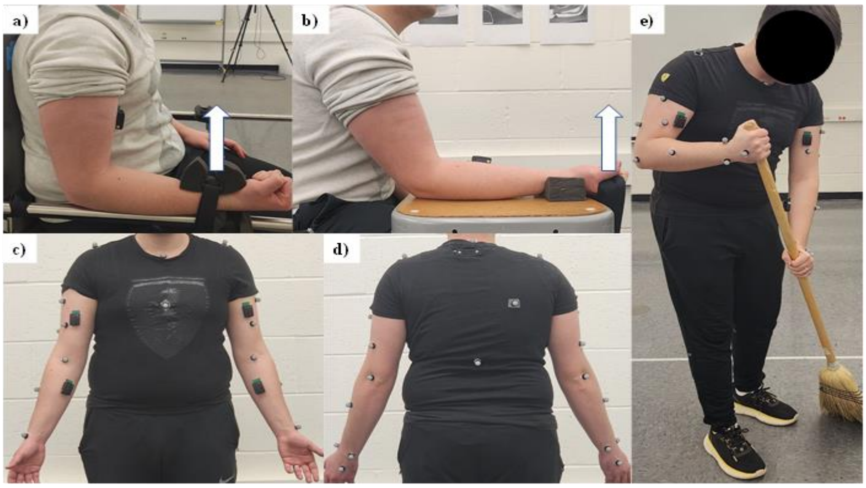

Fig. 2. Dynamic tests are given as percentage of MVC for the software; a. MVC position for BB, b. MVC position for FCR, c. EMG sensor locations and body marker locations (anterior), d. EMG sensor locations and body marker locations (posterior), and e. sweeping exercise. (Arrows indicate the direction of force applied against the resistance.).

$$\%\mathrm{MVC} = \frac{\mathrm{iEMG}}{\mathrm{MVC}} \text{ X } 100\%. \quad \textbf{(5)}$$

For the data collection, in addition to using EMG modules, Vicon Nexus, with the help of the MATLAB pipeline, captured the kinematic data while the subjects were performing both static and dynamic trials. The data synchronization was employed through the use of the Delsys Trigger Module and a Vicon Lock+ device. The Vicon motion capture system with 10 Vicon Vantage V5 cameras (Vicon Motion Systems, Oxford, UK) was used to track reflective markers attached to the subject's skin or clothing and capture upper limb joint angles. Camera data was collected at a frequency of 100 Hz. Prior to the data collection, the cameras were calibrated using the Vicon Active Wand across the entire laboratory volume. This procedure ensured precise marker tracking during both static and dynamic trials. Tight activewear was worn to minimize clothing movement, and 25 body markers, each with a 14mm diameter, were attached to the subject's body, as shown in *Fig. 2.c* and *Fig. 2.d*. Two anatomical markers were attached to the left and right medial epicondyle (LMEP and RMEP) during static calibration and removed for dynamic trials [31]. The static calibration trial involved the subject standing for a short duration of about 1 to 2 seconds, allowing the Vicon Nexus system to capture a static frame. Subjects performed a sweeping exercise, and each subject performed five trials, and each trial was performed for around 5 seconds, as shown in *Fig. 2.e*.

3 | Data Processing

The collected EMG and kinematic data were processed to extract relevant information. EMG Works Analysis software was used to digitally filter, full wave rectify, and smooth the EMG data, which was then normalized using the RMS value obtained during the MVC with a sliding window length of 250 ms and 50% overlap. Joint angles, velocities, and accelerations were calculated from the kinematic data using Vicon Nexus and MATLAB pipeline. The quality of the data was rigorously monitored during the data collection; further details are provided in Section 2.2. After the motion capture data was collected, gap-filling procedures were implemented for the collected marker data to ensure the final data quality, employing pattern fill and rigid body fill methods for larger gaps and spline fill for smaller gaps. The processed data was exported to an Excel csv file.

3.1| Data Pre-Processing

The collected data was pre-processed before creating the model. Each subject had at least five dynamic trials, and the joint angle of both elbows and EMG data were calculated from each trial. The average angles of the left and right arms were calculated by finding the five maximum and minimum values. Raw EMG data was amplitude normalized for each trial with the peak MVC value of the specific muscle group. The maximum percentage of work for BB and FCR muscle groups was also determined. The simplified data of ten subjects with their weights and heights were represented in *Table 1* and then used in the CCR model to find the efficiency.

Table 1. Pre-processed data for DEA analysis.

DMU	Trial	Left Elbow Angle	Right Elbow Angle	Left BB (%)	Left FCR (%)	Right BB (%)	Right FCR (%)
1	5	64.16	51.97	20.62	11.82	17.02	27.95
2	5	37.59	43.07	22.62	19.38	18.11	45.54
3	5	44.51	46.25	19.37	14.85	6.57	15.96
4	5	58.39	48.1	7.11	9.6	7.82	15.03
5	5	51.8	59.81	24.48	17.91	20.88	12.19
6	5	34.84	44.07	32.68	13.26	35.57	45.24
7	5	57.49	65.61	39.05	49.47	28.2	44.8
8	5	41.59	54.9	24.8	34.54	33.7	18.03
9	5	50.1	45.39	50.79	24.69	30.18	16.29
10	5	61.21	55.49	14.35	19.55	26.57	38.65

4| Analysis and Result

Muscle activation and arm angle can be used to evaluate how efficiently someone is executing a task. Most people perceive those who employ the least amount of muscular activation and have the best arm angles to be more efficient. A higher level of production and a lower chance of injury or physical strain can result from optimizing these variables. The DEA analysis is performed in multiple phases: problem formulation phase and SIMO model analysis. *Table 1* displays the data for each subject as well as the input and output of the DEA model.

4.1 | Single Input Multiple Output Model Analysis

The SIMO model is a type of DEA model that measures the relative efficiency of DMUs with respect to a single input and multiple outputs. In the SIMO model, each DMU takes a single input and produces multiple outputs. The goal of the model is to find the weights of the outputs that maximize the efficiency of each DMU while keeping the input constant. The efficiency of a DMU is calculated as the ratio of its weighted sum of outputs to the weighted sum of outputs of the most efficient DMU in the sample.

4.1.1 | Left elbow angle and Left BB EMG data as output

For SIMO model analysis, take the trial number as input and elbow joint angle and EMG value of the BB muscle group as output for the left side. As a result, the linear programming model for the first DMUs (subject) on output efficiency is applied by applying the data of *Table 2* in *Eq. (1)-(4)*.

Table 2. Single input and multiple output DEA model (Left Elbow Angle and BB EMG).

DMU	Input	Output	
	Trial	Left Elbow Angle (deg)	Left BB (%)
1	5	64.16	20.62
2	5	37.59	22.62
3	5	44.51	19.37
4	5	58.39	7.11
5	5	51.8	24.48
6	5	34.84	32.68
7	5	57.49	39.05
8	5	41.59	24.8
9	5	50.1	50.79
10	5	61.21	14.35

The objective function

$\max z = 64.16\lambda_1 + 20.62 * \lambda_2 + 0 * \lambda_3.$

Subject to

$-64.16\lambda_1 - 20.62\lambda_2 + 5 * \lambda_3 \geq 0,$

$-37.59\lambda_1 - 22.62\lambda_2 + 5 * \lambda_3 \geq 0,$

$-44.51\lambda_1 - 19.37\lambda_2 + 5 * \lambda_3 \geq 0,$

$-58.39\lambda_1 - 7.11\lambda_2 + 5 * \lambda_3 \geq 0,$

$-51.80\lambda_1 - 24.48\lambda_2 + 5 * \lambda_3 \geq 0,$

$-34.84\lambda_1 - 32.68\lambda_2 + 5 * \lambda_3 \geq 0,$

$-57.49\lambda_1 - 39.05\lambda_2 + 5 * \lambda_3 \geq 0,$

$-41.59\lambda_1 - 24.80\lambda_2 + 5 * \lambda_3 \geq 0,$

$-50.10\lambda_1 - 50.79\lambda_2 + 5 * \lambda_3 \geq 0,$

$-61.21\lambda_1 - 14.35\lambda_2 + 5 * \lambda_3 \geq 0,$

$0 * \lambda_1 + 0 * \lambda_2 + 5 * \lambda_3 = 1,$

$\lambda_1, \lambda_2, \lambda_3 \geq 0.$

Results from the DEA model, using MATLAB and the fmincon function, indicate that DMU-1 operates at 73.98% efficiency compared to the most efficient DMU while keeping its input constant. Individual efficiencies for each DMU were obtained through separate goal functions and constraints, with efficiencies ranging from 64% to 100%, as shown in *Table 3*. DMUs with efficiencies of 100% are considered to be efficient and operate at the minimum possible level, given their inputs and outputs. Individuals who use less muscle activation and a more optimal arm angle while performing their work tend to be more efficient [16]. The 2nd, 4th, and 6th subjects are the efficient ones shown in *Table 3*. The remaining DMUs have efficiencies ranging from 64.22% to 96.37%, which means they are operating at varying levels of efficiency compared to the most efficient DMUs.

Table 3. Efficiency of DMUs (left elbow angle vs BB).

DMU	1	2	3	4	5	6	7	8	9	10
Efficiency (%)	73.98	100	96.37	100	80.26	100	64.22	90.75	69.54	84.43

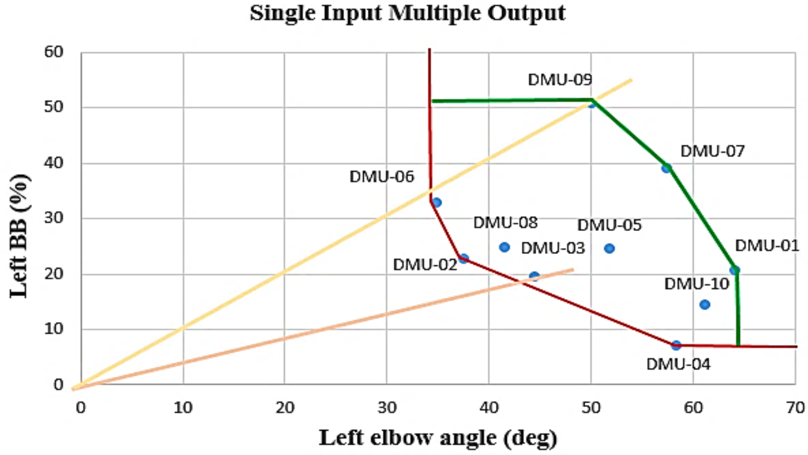

Fig. 3. Left elbow angle vs BB graphical representation.

We could generate the graph shown in *Fig. 3* for the left-hand angle and BB by graphing the data points of the left side from *Table 2*. The positions on the graph represented by DMUs 2, 4, and 6 demonstrate a level of performance that is superior to all other DMUs. It is possible to visualize the efficient DMUs and their performance scores by plotting the left-hand data and connecting the efficient points with a convex curve. This curve is called the efficient frontier, and DMUs that fall on this curve are considered to be 100% efficient, which is the red curve shown in *Fig. 3*. In contrast, DMUs that fall outside of the efficient frontier are considered inefficient. When all the DMUs are plotted on a graph, the efficient (red curve) and inefficient (green curve) frontiers create a convex hull that encompasses all the DMUs. It is also clear from the graphical depiction that every ineffective DMU may discover a role model from whom they can learn how to perform more effectively without considerable ergonomic risk.

From *Fig. 3*, if we draw a straight line from the basepoint through the DMU-03, we can see that the efficient frontiers convex curve at a specific point, and from that point of intersection, we can say that DMU-02 and DMU-04 are close to DMU-03. But as the DMU-02 is the closest one, this is the role model for DMU-03. Similarly, for DMU-09, DMU-06 is the role model. By drawing a straight line through all other DMUs, we can conclude which efficient DMU is the role model for which inefficient DMU.

4.1.2 | Right elbow angle and BB EMG data as output

For SIMO model analysis, take trail number as input and elbow joint angle and EMG value of the biceps muscle group as output for the right side.

As a result, the linear programming model for the first DMUs (subject) on output efficiency is applied by applying the data of *Table 4* in *Eq. (1)-(4)*.

Table 4. Single input and multiple output DEA model (right elbow angle and BB EMG).

DMU	Input	Output	
	Trial	Right Elbow Angle	Right BB
1	5	51.97	17.02
2	5	43.07	18.11
3	5	46.25	6.57
4	5	48.1	7.82
5	5	59.81	20.88
6	5	44.07	35.57
7	5	65.61	28.2
8	5	54.9	33.7
9	5	45.39	30.18
10	5	55.49	26.57

The objective function

$$\max z = 51.97\lambda_1 + 17.02 * \lambda_2 + 0 * \lambda_3. \tag{5}$$

Subject to

$$-51.97\lambda_1 - 17.02\lambda_2 + 5 * \lambda_3 \geq 0,$$
$$-43.07\lambda_1 - 18.11\lambda_2 + 5 * \lambda_3 \geq 0,$$
$$-46.25\lambda_1 - 6.57\lambda_2 + 5 * \lambda_3 \geq 0,$$
$$-48.1\lambda_1 - 7.82\lambda_2 + 5 * \lambda_3 \geq 0,$$
$$-59.81\lambda_1 - 20.88\lambda_2 + 5 * \lambda_3 \geq 0,$$
$$-44.07\lambda_1 - 35.57\lambda_2 + 5 * \lambda_3 \geq 0,$$
$$-65.61\lambda_1 - 28.2\lambda_2 + 5 * \lambda_3 \geq 0,$$
$$-54.9\lambda_1 - 33.7\lambda_2 + 5 * \lambda_3 \geq 0,$$
$$-45.39\lambda_1 - 30.18\lambda_2 + 5 * \lambda_3 \geq 0,$$
$$-55.49\lambda_1 - 26.57\lambda_2 + 5 * \lambda_3 \geq 0,$$
$$0 * \lambda_1 + 0 * \lambda_2 + 5 * \lambda_3 = 1,$$
$$\lambda_1, \lambda_2, \lambda_3 \geq 0.$$

DEA can evaluate DMUs, and applying DEA equations in MATLAB with the fmincon function allows for efficiency determination. DMUs, in this case, had efficiencies ranging from 60% to 100%, with DMUs 2 and 3 being most efficient at 100%. DMU-1 was 84.82% efficient, and the remaining DMUs had efficiencies ranging from 65.65% to 97.73%, as shown in *Table 5*.

Table 5. Efficiency of DMUs (right elbow angle vs BB).

DMU	1	2	3	4	5	6	7	8	9	10
Efficiency (%)	84.82	100	100	95.63	73.30	97.73	65.65	78.45	94.89	77.62

We could generate the graph shown in *Fig. 4* for the right-hand angle and BB by graphing the data points of the left side from *Table 4*. The positions on the graph represented by DMUs 2 and 3 demonstrate a level of performance that uses less muscle activation and a more optimal arm angle that is superior to all other DMUs and forms a convex curve, which is the red curve shown in *Fig. 4*. This curve is called the efficient frontier, and DMUs that fall on this curve are 100% efficient. All other points falling above the curve, like the previous one, are considered inefficient. When all the DMUs are plotted on a graph, the efficient (red curve) and inefficient (green curve) frontiers create a convex hull that encompasses all the DMUs. Drawing a straight line from the basepoint through DMU-01 in *Fig. 4* allows us to identify the intersection point with the efficient frontier curve, indicating that DMU-02 and DMU-03 are close to DMU-01. DMU-02 is the closest and, therefore, serves as the role model for DMU-01. Similarly, drawing lines through other DMUs can help identify which efficient DMU serves as a role model for each inefficient DMU.

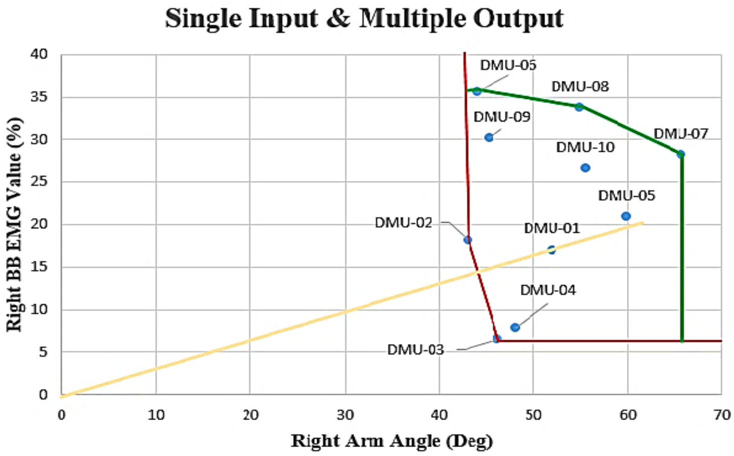

Fig. 4. Right elbow angle vs BB graphical representation.

By altering the output, we can identify the efficient and non-efficient frontiers in every case of left and right hand, such as Angle & FCR as output, BB & FCR as output, and Angle, BB & FCR as output. This process remains consistent for all input and output levels.

All inefficient individuals from the SIMO model may learn how to become more efficient from their closest role model, including the direction or angle they should move their arm when performing a certain job to avoid any job-related muscle problems. By adopting better work techniques that minimize muscle activation and optimize arm angle, workers can improve their efficiency, reduce the risk of musculoskeletal disorders, and increase productivity.

Optimizing work methods, especially in worker arm usage, significantly improves efficiency and productivity. Adopting superior work strategies learned from a role model minimizes muscle activation and optimizes arm angles. This not only enhances efficiency but also reduces the risk of musculoskeletal issues. Learning from a role model is a valuable approach to improving overall job performance while prioritizing health and safety in the workplace.

5 | Discussion

SIMO models result in efficient and inefficient frontiers, creating a convex hull for all DMUs. Efficient workers use optimal arm angles and exhibit less muscle activation, leading to higher efficiency. Workers can learn from role models to improve their techniques and efficiency, which reduces the risk of musculoskeletal problems and enhances output. Superior work procedures that limit muscle activation and optimize arm angle can increase worker efficiency. Optimizing work methods can increase productivity and efficiency in every job and profession. One area that can be improved is worker arm usage while carrying out their duties. By using superior work strategies, workers can improve their productivity, decrease their chance of developing musculoskeletal illnesses, and increase their efficiency. Poor work practices over time can result in muscular aches, strain, and injury, which can reduce output and be uncomfortable. By learning from a role model, workers can improve their work habits and increase their productivity and safety. Using the right technique can help employees avoid putting undue pressure on their muscles and joints, which lowers their chance of suffering from illnesses such as tendinitis, carpal tunnel syndrome, and tennis elbow. Overall, workers must prioritize their health and safety by using the right work practices, which can improve their overall job performance.

Although the current DEA offers promising results in the field of ergonomics, we recognize several limitations in our study. Variability in participant performance of static MVC movements and dynamic exercises, as well as in trial conditions, may introduce bias into the data collection. Additionally, some of our subjects had no prior experience with motion capture systems, which might affect the generalizability of our results. Furthermore, in future studies, we plan to apply our DEA method to a variety of dynamic tasks and with larger sample sizes to validate further and extend our findings.

6 | Conclusions

DEA can be used to evaluate the effectiveness and efficiency of DMUs, including individual workers, based on ergonomic risk and performance. Incorporating kinematics and EMG data into the DEA framework can provide a more thorough and impartial evaluation of worker performance. In the context of worker health and safety, an innovative framework leveraging the CCR model of DEA can evaluate ergonomic risk and performance. This approach categorizes employees into efficient and average frontiers, identifying role models for improvement. To enhance worker performance evaluation, kinematics data, measuring body component motions during job activities, can be incorporated alongside EMG data. This comprehensive approach distinguishes between efficient and struggling employees, allowing the DEA model to identify best practices and role models for others to follow. Muscle activation, indicating the level of muscular contraction needed for a task, is a key factor affecting energy expenditure and efficiency. Optimal arm angles can also improve productivity by minimizing unnecessary movements. By identifying best practices and role models for workers to follow, they can increase their efficiency and output while reducing the risk of musculoskeletal problems. For further studies, we can 1) explore the potential of Vicon Motion Capture in analyzing and identifying specific ergonomic advantages in various industries, including healthcare, construction, and manufacturing 2) extend the use of DEA beyond the supply chain and facility design to assess and improve organizational performance in other areas, such as marketing, finance, and human resources and 3) explore the potential of the DEA method in identifying and addressing other musculoskeletal problems and investigate the effectiveness of interventions aimed at improving employee performance and reducing the risk of injury.

Conflicts of Interest

All co-authors have seen and agreed with the contents of the manuscript, and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

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