Computers, Materials & Continua
DOI:10.32604/cmc.2021.017548
Article

An Optimized Framework for Surgical Team Selection

Hemant Petwal* and Rinkle Rani

Department of Computer Science and Engineering, Thapar Institute of Engineering and Technology, Patiala, 147004, India
*Corresponding Author: Hemant Petwal. Email: hemant.petwal@thapar.edu
Received: 02 February 2021; Accepted: 11 April 2021

Abstract: In the healthcare system, a surgical team is a unit of experienced personnel who provide medical care to surgical patients during surgery. Selecting a surgical team is challenging for a multispecialty hospital as the performance of its members affects the efficiency and reliability of the hospital's patient care. The effectiveness of a surgical team depends not only on its individual members but also on the coordination among them. In this paper, we addressed the challenges of surgical team selection faced by a multispecialty hospital and proposed a decision-making framework for selecting the optimal list of surgical teams for a given patient. The proposed framework focused on improving the existing surgical history management system by arranging surgery-bound patients into optimal subgroups based on similar characteristics and selecting an optimal list of surgical teams for a new surgical patient based on the patient's subgroups. For this end, two population-based meta-heuristic algorithms for clustering of mixed datasets and multi-objective optimization were proposed. The proposed algorithms were tested using different datasets and benchmark functions. Furthermore, the proposed framework was validated through a case study of a real postoperative surgical dataset obtained from the orthopedic surgery department of a multispecialty hospital in India. The results revealed that the proposed framework was efficient in arranging patients in optimal groups as well as selecting optimal surgical teams for a given patient.

Keywords: Multi-objective optimization; artificial electric field algorithm; mixed dataset clustering; surgical team; strength Pareto

1 Introduction

During a preoperative procedure, surgical team members, surgical specialty and experience, and coordination among the members play essential roles. Although various factors can affect surgical procedures, positive outcomes mainly depend on the individual surgical team members. Appropriate coordination and cooperation among those can reduce unavoidable conflicts during the procedures [1]. Hence, the selection of an optimal surgical team is indispensable for a rapid patient recovery, decreased complications, and more favorable surgical management. However, the selection process is a considerably time-consuming and difficult task [2]. In recent years, several studies have examined the performance of surgical team members. Many vital factors, such as understanding diagnostic complications and patient characteristics, and the surgical practice environment, can result in more satisfactory outcomes. In the field of medicine, appropriate management of surgical care is a difficult task as most surgical complications occur during intra operative surgical care [3]. An efficient team can help in providing effective healthcare services [4]. Hospitals and physicians always focus on providing a safe environment for patients and enhancing their wellbeing [5]. A study investigated human factors associated with operating rooms and analyzed the relationship between their poor performance and the surgical procedures outcomes [4]. Similarly, several studies adopted approaches such as malpractice claim analysis [6], root cause analysis [7], and prospective analysis [8] to reduce intra operative surgical complications. Although these studies tried to analyze the relationship between the performance of operating room and outcomes of surgery, however, contribution of significant factors affecting the performance of operating room were not considered [3]. Studies examining factors such as teamwork in the operating room [9] and intensive care [10] focused on the effect of coordination and synergy among surgical team members. These studies have indicated the necessity and significance of surgical team selection procedure. As performing surgical procedures is often a risky and uncertain task, therefore high synergy is always expected among team members possessing different levels of experience and expertise. Various factors such as availability of surgeons, limitation of resources, and time etc. affect the surgical team selection in a multispecialty hospital; thus, selection of the surgical team is a challenging task [11]. In a surgical team, different responsibilities are assigned to different individuals [12]. As the responsibilities and the individuals to whom responsibilities are assigned change frequently with time, thus selecting an efficient team for the desired activity, considering time and resource limitation, becomes a complicated procedure. All the aforementioned studies have focused on personnel preferences for the day, shift, and units. However, none of these studies have considered the history of the surgical team, characteristics of patients, and feedback of patients who underwent surgery in the past. In this study, an optimal framework based on the characteristics of patients, history of the surgical team, and the feedback of previous surgical patients is proposed to assist in decision-making for the selection of optimal surgical teams. An optimal list of surgical teams contains more than one suitable surgical team that can be assigned to a surgical patient according to their availability.

The rest of the paper is organized as follows. Section 2 presents an overview of the existing literature. Section 3 describes preliminary and background algorithms. Section 4 discusses the proposed framework in detail. Section 5 presents a detailed case study of the orthopedic surgery department at a multispecialty hospital in India. Section 6 summarizes the findings of this research and provides concluding remarks.

2 Related Work

2.1 Literature Review

In a modern healthcare system, the provision of high-quality surgical services typically depends on symptoms of various patients. Classifying patients on the basis of their symptoms assist the decision-makers in identifying the target patient and making corresponding remedial decisions [13]. In recent years, several methods have been proposed by the authors for clustering of patients. One of the studies used k-means clustering algorithm to partition the patients based on their health status [13]. Another study used a multilayer clustering approach for partitioning of Alzheimer disease patients into male and female groups [14]. In addition, few studies have used agglomerative hierarchical clustering for partitioning of patients based on presence of comorbidities such as chronic pain and mental illness; obesity and mental illness; cancer;

diabetes and renal disease [15,16]. A Bayesian nonparametric clustering approach was applied to divide patients having cancer into sub-groups to measure their anxiety and depression scores before psychotherapy [17]. Further, in a study authors proposed a hierarchical clustering algorithm incorporating genetic concept for partitioning the patients with or without depression [18]. Furthermore, many intelligent nature-inspired algorithms have also been proposed for data clustering. A study proposed a hybrid algorithm combining particle swarm optimization (PSO) and artificial bee colony (ABC) algorithms for data clustering [19]. Additionally, k-means [20] and k-harmonic means [21]—clustering algorithms have been -used for performing—clustering of mixed datasets. The functioning of most of these clustering algorithms is dependent on the predefined number of clusters. However, in real-life problems, for most of the datasets the number of clusters is not known beforehand. Hence, the accurate estimation of an optimal number of clusters is a challenging task, and can affect the performance of a clustering algorithm also. Therefore, several algorithms, such as the gravitational search algorithm [22], harmony search algorithm [23], and differential evolution algorithm [24], have been proposed for automatic clustering to address the aforementioned challenge. Automatic clustering algorithms require no prior information regarding the number of clusters. Instead, they evaluate the optimal number of clusters based on the dataset only. In this paper, an efficient clustering algorithm for mixed datasets based on the artificial electric field algorithm (AEFA) [25] is proposed to categorize patients based on their characteristics (symptoms). A recent study utilized k-prototypes algorithm for partitioning of patients and genetic algorithm (GA) for the selection of optimal surgical team [5]. Although the study reported favorable outcomes, it focused only on the complication ratio for the surgical team selection. However, the success of a surgical procedure depends on various factors also such as a lower surgical readmission rate, lower mortality and complication rates, and higher patient satisfaction (surgical feedback) etc. Therefore, this study considered the feedback of patients who underwent surgery in the past along with complication rates to select an optimal surgical team. Further, the GA [26,27] utilized by Ebadi et al. [5] is likely to experience premature convergence and diversity loss. In addition, Srinivas et al. [28], Gu et al. [29], Hassanzadeh et al. [30], Yuan et al. [31], and Nobahari et al. [32] have proposed several meta-heuristic approaches to prevent premature convergence. These algorithms have been found efficient in finding the optimal solution in a single computation. In this paper, an improved AFEA for multi-objective optimization is proposed to select optimal surgical teams. To the best of our knowledge, no study has focused on considering surgical feedback along with complication rates for selecting optimal surgical teams by utilizing AEFA. Tab. 1 summarizes the existing work related to surgical decision-making.

Table 1: Summary of the existing work related to surgical decision making

Author(s)	Objective/Work performed	Technique proposed/used	Performance parameters	Research Gap(s) identified
Gamberger et al. [14]	To partition patients with Alzheimer disease into homogeneous subgroups	A multilayer clustering approach	Clinical dementia rating score	The segmentation of patients with cognitive problems was not considered.
Li et al. [17]	To partition patients with cancer into subgroups for measuring their anxiety and depression scores	Bayesian nonparametric clustering approach	Within cluster contrast	The proposed algorithm was sensitive to the initial sample size.

(Continued)

Table 1: Continued

Author(s)	Objective/Work performed	Technique proposed/used	Performance parameters	Research Gap(s) identified
Yu et al. [18]	To identify the subgroups of patients with and without depression	1. Hierarchical clustering based on the genetic concept 2. Distance matrix	1. Approximately unbiased probability value 2. Bootstrap probability value	This study considered the genetic data of a specific population only.
Karthikeyan et al. [19]	Proposed hybrid PSO and ABC algorithm for data clustering.	Hybrid PSO and ABC	1. Accuracy 2. Classification error percentage	The proposed algorithm focused on numeric attributes only.
Ahmad et al. [20]	Proposed k-mean clustering for mixed data.	K-mean Clustering	1. Micro-Precision 2. Micro-Recall	The centroid initialization problem persists.
Ahmad et al. [21]	Proposed k-harmonic mean for mixed data.	K-Harmonic clustering algorithms	1. Intra-cluster distance 2. Inter-cluster distance	The proposed algorithm focused on numeric attributes only.
Kumar et al. [22]	Proposed automatic data clustering and feature selection using the gravitational search algorithm.	Gravitational search algorithm	1. Silhouette index 2. Classification error	The proposed algorithm focused on numeric attributes only.
Kumar et al. [23]	Proposed automatic data clustering using an adaptive harmony search algorithm.	Adaptive harmony search algorithm	1. Inter-cluster distance 2. Intra-cluster distance 3. Trace	The proposed algorithm focused on numeric attributes only.
Srinivas et al. [28]	Proposed genetic algorithm based on nondominant sorting for multi-objective optimization	Nondominant sorting genetic algorithm	Chi-square test	The proposed algorithm exhibited a slow convergence rate.
Gu et al. [29]	Proposed an evolutionary algorithm based on the projection of the current nondominant solutions and equidistance interpolation for multi-objective optimization	Dynamic weight design method with MOEA/D	1. Benchmark functions 2. Mean 3. Standard deviation 4. Inverted generational distance	The algorithm lacked efficiency in solving higher-dimensional complex problems.
Hassanzadeh et al. [30]	Proposed a gravitational force-based algorithm for multi-objective optimization	Multi-objective gravitational search algorithm	1. Spacing metric 2. Generational distance metric	The algorithm experienced diversity loss in solving higher-dimensional complex problems.
Yuan et al. [31]	Proposed a gravitational search algorithm based on strength Pareto for multi-objective optimization.	Strength Pareto gravitational search	1. Convergence metric 2. Space metric 3. Generational distance metric 4. Diversity metric	Population diversity requires further improvement.

(Continued)

Table 1: Continued

Author(s)	Objective/Work performed	Technique proposed/used	Performance parameters	Research Gap(s) identified
Nobahari et.al. [32]	Proposed a multi-objective gravitational search algorithm based on nondominant sorting for power transformer design	Nondominant sorting gravitational search algorithm	Normalized arithmetic mean	The algorithm experienced scalability loss while dealing with complex cases of power transformer design.

2.2 Our Contribution

(1) A decision-making framework is proposed to assist medical practitioners while selecting optimal surgical teams for a given patient.
(2) Two population-based meta-heuristic algorithms are proposed for clustering of mixed datasets and multi-objective optimization, which are used for the partitioning of patients and the selection of optimal surgical teams, respectively.
(3) The proposed algorithms are validated using a real surgical dataset of a multispecialty hospital in India.

3 Preliminary and Background

This section briefly discusses the basic concepts of partitioning clustering, distance measure for mixed datasets, multi-objective optimization, and artificial electric field algorithm (AEFA).

3.1 Partitioning Clustering

In data clustering, partitioning clustering arranges data points into distinct clusters (CLC_i). Let us consider a dataset $D = \{D_1, D_2, D_3, \ldots, D_n\}$ of n datapoints each with d attributes. For example, $D_j = (D_{j1}, D_{j2}, \ldots, D_{jd})$ is a vector representing the j^{th} datapoint, where D_{ji} represents the i^{th} attribute of D_j. The partitioning clustering algorithm should satisfy the following condition:

$$CLC_i \neq \phi, \quad i = 1, 2, \ldots, N_k, \quad \sum_{i=1}^{N_k} CLC_i = D, \quad CLC_i \cap CLC_j \neq \phi \forall\, i, j$$

where, N_k represents the number of clusters.

3.2 Distance Measure for Mixed Datasets

The closeness between a data point and clusters is measured by computing the distance between them. The distance measure confirms homogeneity among the data points of a cluster and heterogeneity between different clusters. Arranging a mixed dataset into distinct clusters is a challenging task. In this paper, the distance measure (ϑ) [20] is used to compute the distance between the i^{th} data point (P_i) and j^{th} centroid (CLC_j) as follows:

$$\vartheta\left(P_i, CLC_j\right) = \sum_{t=1}^{m_r} \left(w_t \left(P_{it}^r - CLC_{jt}^r\right)\right)^2 + \sum_{t=1}^{m_c} \Omega\left(P_{it}^c, CLC_{jt}^c\right)^2 \tag{1}$$

where $\left(P_{it}^{r} - CLC_{jt}^{r}\right)$ represents the distance between the t^{th} numeric attribute value of P_i and the centroid (CLC_{jt}^{r}), $(P_{it}^{c}, CLC_{jt}^{c})$ represents the distance between the t^{th} categorical attribute value of P_i and centroid (CLC_{jt}^{c}), and w_t implies the significance of the t^{th} numeric attribute. The distance between the two values of a categorical attribute is measured by computing the co-occurrence of these values with the values of other categorical attributes.

3.3 Multi-objective Optimization

A multi-objective problem (MOOP) can be a minimization or a maximization problem. It involves O distinct target objectives that are defined as follows:

Minimize/Maximize: $\text{Fitness}\ (P_r) = [\text{Fitness}_i\,(P_r)\,,\, i = 1, 2, \ldots, O]$

Subject to constraints: $\begin{cases} EC_j\,(P_r) \le 0, & j = 1, 2, \ldots, j \\ IC_k\,(P_r) \le 0, & k = 1, 2, \ldots, k \end{cases}$

where, $\text{Fitness}_i\,(P_r)$ represents the i^{th} objective function of the P_r^{th} solution, and $EC_j\,(P_r)$ and $IC_k\,(P_r)$ represent j^{th} equality and k^{th} inequality constraints, respectively. In MOOP, Pareto dominance theory [31] is utilized to determine optimal solutions in global search space.

3.4 Artificial Electric Field Algorithm (AEFA)

AEFA, a population-based meta-heuristic algorithm, simulates Coulomb's law of electrostatic attraction force (EAF) and the law of motion. Each candidate solution in AEFA is represented as a charged particle. The charge present on each charged particle assists in evaluating the performance of a candidate solution. Because of EAF, each charged particle attracts another charged particle, resulting in the global movement of all charged particles toward a heavier charged particle.

4 Proposed Framework

This section provides a detailed description of the proposed framework. The proposed framework consists of two modules: surgical history management (SHM) and surgical team selection (STS). The SHM module involves two activities: (1) clustering of existing surgical patients based on their characteristics and (2) filtering of existing surgical team details. The STS module produces an optimal list of surgical teams for a given patient. The SHM module is designed to assist the STS module in decision-making. Fig. 1 presents the workflow of the proposed framework.

4.1 Surgical History Management (SHM) Module

Surgical history is a vital aspect of medical records and includes the social and demographic information of surgical patients, the details of surgical teams, and the outcomes of diagnostic and procedural tests. For multispecialty hospitals that provide surgical services to numerous patients, efficient management of surgical records is essential. An efficiently organized surgical history helps hospitals to enhance their patient care and resource efficiency. To utilize these surgical records, the following two activities are performed in the SHM module.

4.1.1 Clustering of the Existing Surgical Patients

Arranging existing surgical patients in disjoint clusters based on their characteristics can help hospitals to find a suitable subgroup for a newly referred surgical patient. In this study, an efficient data clustering algorithm for mixed datasets [33] is proposed to cluster surgical patients. The proposed clustering algorithm (Algorithm 1) based on the AEFA focuses on finding optimal clusters automatically. The steps of the proposed clustering algorithm are as follows:

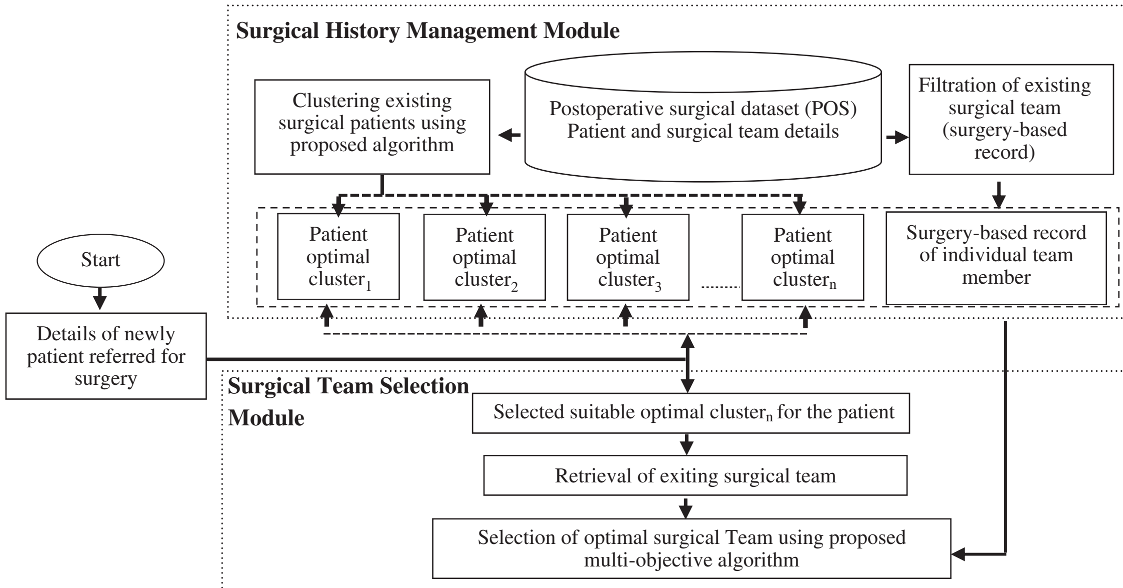

Figure 1: Workflow of the proposed framework

A. Improved Electrostatic Force Computation and Velocity Update

In a traditional AEFA, the total electrostatic attraction force (TEAF; Eq. (2)) on i^{th} charged particle is computed by multiplying a random number to EAF exerted by j^{th} charged particles on it. This force affects acceleration and velocity, thus resulting in the global movement of all charged particles. Furthermore, the velocity (Eq. (4)) of i^{th} charged particle is updated by multiplying a random number to its existing velocity value. These random numbers add stochastic behavior in an algorithm's search process, resulting in an imbalance between exploration and exploitation, thus causes the algorithm to trap in local optima. To maintain a balance between exploration and exploitation, instead of using only random number we have considered charge of a charged particle (q_i) also. The charge of a charged particle controls the stochastic behavior during the computation of TEAF and velocity; this, in turn, reduces the acceleration and velocity values of the charged particle, thus balancing exploration and exploitation. The modified equations (Eqs. (3) and (5)) are shown as follows:

$$TEAF_i^D(T) = \sum_{j=1, j\neq i}^{N} rand() * EAF_{ij}^D(T) \tag{2}$$

$$TEAF_i^D(T) = \sum_{j=1, j\neq i}^{N} \left(rand_i * r_1 + \left(1 - e^{\sqrt{q_i}}\right) * r_2\right) * EAF_{ij}^D(T) \tag{3}$$

$$vel_i^D(T+1) = rand_i * vel_i^D(T) + a_i^D(T) \tag{4}$$

$$vel_i^D(T+1) = \left(rand_i * r_1 + \left(1 - e^{\sqrt{q_i}}\right) * r_2\right) * vel_i^D(T) + a_i^D(T) \tag{5}$$

where, r_1 and r_2 are two non-negative integers and $r_1 + r_2 = 1$. Furthermore, in case of $r_1 = 1$ and $r_2 = 0$, Eqs. (3) and (5), and Eqs. (2) and (4) are treated identically.

B. Selection of Active Centroids

For each candidate solution, active centroids are selected from CLC_{max} centroids based on the following condition:

$$CLC_{ij} = \begin{cases} 1, & THV_{ij} > T_{COV} \\ 0, & Otherwise \end{cases} \tag{6}$$

where, T_{COV} is the cutoff value for each centroid, and is set to a random value between [0,1]. T_{COV} depends on the selection threshold value (THV_{SL}) of a centroid and is computed as follows:

$$T_{COV} = \frac{1}{CLC_{active}} \sum_{l=1}^{CLC_{active}} THV_{SL_l},\ THV_{SL} = \sqrt{\frac{1}{n_{SL}}\left(\sum_{i=1}^{m_r} \Omega\left(P_i^r, CLC_{SL}^r\right)^2\right) + \left(\sum_{i=1}^{m_c} \Omega\left(P_i^c, CLC_{SL}^c\right)^2\right)} \tag{7}$$

where, CLC_{active} represents the number of active centroids in each candidate solution.

Algorithm 1: Proposed algorithm for clustering surgical patients

---

Input: A postoperative surgical dataset
Output: Patients with their optimal clusters
Begin
Define the maximum number of iterations ($MaxIT$), the maximum number of clusters (CLC_{max}), population size (P_S), selection threshold (THV_{SL}) and cutoff threshold (T_{COV})
Compute the dimension and randomly initialize a population of patients (PT) as a cluster centroid from the dataset
Initialize iteration counter, $I_t = 1$
While $I_t < MaxIT$ **do**
  for $i = 1$ to P_S **do**
    for $j = 1$ to CLC_{max} **do**
      if ($THV_{ij} > T_{COV}$) **then**
        Verify and activate the centroid PT_i^j by using Eq. (6)
      else
        PT_i^j is set to inactive
      end if
    end for
    for each patient (PT_i) in given mixed dataset
    A. Compute the distance between PT_i and active PT_i^j by using Eq. (1) and assign PT_i to the nearest active PT_i^j
    B. Verify and reinitialize the empty PT_i^j as described in Section 4.1.1
    end for

(Continued)

end for
Update the population by following the AEFA algorithm (Section 4.1.1). The fitness function in Eq. (8) and the distance measures in Eq. (1) are used to direct the exploration process.
Update THV_{SL} and T_{COV} for each PT in the updated population by using Eq. (7)
$I_t = I_t + 1$
end while
Return patients (PT) and their optimal clusters.

C. Validation of Empty Clusters

A centroid having less than two data points is termed as an empty cluster. In such cases, the corresponding centroid of the candidate solution is reinitialized, and m/CLC_{active} data points are assigned to each nearest active centroid.

D. Computation of Fitness

The efficiency of a clustering algorithm depends on the cluster validation criteria. In this study, we have used silhouette index (SI) criteria for cluster validation. The fitness of the candidate solution is computed as follows:

$$Fitness\,(QP_i) = SI\,(QP_i) * \frac{CLC_{max} - CLC_{active}}{CLC_{active} + 1}, \quad SI\,(QP_i) = \frac{Mean_g - Mean_h}{\max\left(Mean_g,\, Mean_h\right)} \tag{8}$$

where, $Mean_g$ represents the mean distance to other data points in the same cluster (mean intra-cluster distance), and $Mean_h$ represents the mean distance to other data points in different clusters (mean inter-cluster distance). A candidate solution with the minimum fitness is selected as an optimal solution.

4.1.2 Filtration of the Existing Surgical Team

In this section, a postoperative surgical dataset is considered as an input. Subsequently, on the basis of the required surgery type (e.g., orthopedic surgery, neurosurgery, and pediatric surgery etc.), the details of existing surgical teams are retrieved. A surgical team involves a surgeon, a nurse circulator, and an anesthesiologist. For each retrieved surgical team, additional information such as the complication rate and patient's surgical feedback rating -are computed and stored in a database. This stored information helps decision makers in optimizing the process of surgical team selection.

4.2 Surgical Team Selection (STS) Module

This module is invoked when the proposed framework receives details of a new surgical patient. Subsequently, an optimal cluster is selected for the new patient. The details of the corresponding surgical teams are then retrieved from the selected cluster and processed to obtain the optimal list of surgical teams. In this paper, an efficient meta-heuristic algorithm for multi-objective optimization based on AEFA is proposed to generate an optimal list of surgical teams.

4.2.1 Proposed Multi-objective Optimization Algorithm for Surgical Team Selection

The proposed multi-objective optimization (MOOA) algorithm begins with parameter initialization. Subsequently, the population of candidate solutions is generated. The proposed algorithm has two populations: search population (P_{Search}) and external population ($P_{External}$). The P_{Search}, which contains initial candidate solutions, computes non dominant solutions and stores them in $P_{external}$. The surgical team retrieved in the STS module serves as an initial P_{Search}, and along with the surgical team extracted in the SHM module, it is used to conduct the exploration process of the proposed algorithm. The maximum size of the initial population is computed as follows:

$$P_{SSize} = \sqrt{P_{Comb}} \tag{9}$$

where, $\sqrt{P_{Comb}}$ is the number of possible combinations of surgical teams extracted from the selected suitable patient cluster.

Finally, on the basis of the fitness value of each candidate solution, the best solution is selected. This process is iteratively performed until the convergence condition is satisfied and optimum solutions are obtained. To improve convergence, bounded exponential crossover (BEX) [34] and polynomial mutation operator (PMO) [35] are used in the proposed MOOA. Furthermore, to enhance exploration and exploitation, modifications are introduced in the electrostatic force computation and velocity update (Section 4.1.1) in the proposed MOOA. The proposed MOOA is presented in Algorithm 2.

Algorithm 2: Proposed multi-objective optimization algorithm for surgical team selection

---

Input: Details of the existing surgical teams (obtained from STS and SHM modules)
Output: Optimal list of surgical teams
Begin
Define the search population size (P_{SSize}), external population size (P_{ESize}), and the maximum number of iterations ($MaxIT$)
Initialize the search population (P_{Search}) of the surgical team (ST) obtained from the STS module.
Initialize the external population $P_{External} = \emptyset$ and set an iteration counter $I_t = 1$.
while ($I_t < MaxIT$)
  for each $ST \in P_{Search I_t} U P_{External I t}$
  (i). Compute the fitness ($Fitness\,(ST)$) by using Eqs. (10) and (11)
  (ii). Compute the additional density value *(Density) by* using the k^{th} nearest neighbor algorithm.
  end for
  for each $ST \in P_{Search I_t} U P_{External I t}$ **do**
    if $Fitness\,(ST) < 1$ **then**
$P_{External I t+1} = P_{External I t+1} U \{ST\}$
    end if
  end for
  if (size of $(P_{External I t+1}) < P_{ESize}$), **then**
  $P_{External I t+1} = P_{External I t+1} U \left(\left(P_{Search I_t} U P_{External I t}\right)\left[1: P_{ESize} \left|P_{External I t+1}\right|\right]\right)$
  else
  Compute the additional density values for each non-dominant ST in $P_{External I t+1}$ and delete an ST with the smallest density value.
  end if
  (i). Select surgical team (ST) into the mating pool $P_{I_{t+1}}$ from $P_{Search I t} U P_{External I t+1}$
  (ii). Compute charge, update the velocity and position of POP_{I_t+1}, and obtain the new STs
  (iii). Apply BEX and PMO on population $P_{I_{t+1}}$

(Continued)

for each $ST \in P_{External\,I\,t+1}$ **do**
Compute the additional density value of each ST
end for
Compute the additional density value of each ST in $P_{External\,I\,t+1}$ and perform nondominant sorting
$I_t = I_t + 1$
end while
Return the optimal list of surgical teams (ST)

4.2.2 Fitness Evaluation of the Surgical Team

In this study, two factors are considered to evaluate the performance of a surgical team: complications associated with surgery [5] and patients' surgical feedback rating. Surgical feedback is defined as the experience of patients during the surgical period. In this study, the feedback ratings of existing surgical teams were collected in terms of a surgical team's behavior and activity. The fitness functions are computed as follows:

Minimize

$$Fitness\,(ST) = CompF_t\,(ST)\,, \text{ where } \mathrm{CompF}_t\,(ST) = \alpha * \mathrm{Comp_t}\,(\mathrm{ST}) + (1-\alpha) * noComp_t\,(ST) \quad (10)$$

Maximize

$$Fitness\,(ST) = SF_t\,(ST)$$

where, $\mathrm{CompF}_t\,(ST)$ is a fitness value that represents a combination of complication ratio $Comp_t$ and no-complication ratio $noComp_t$ associated with the surgical team (ST) at time t. SF_t represents surgical feedback rating and is computed as follows:

$$SF_t = \frac{1}{n}\sum_{i=1}^{n}\frac{\sum_{J=1}^{SP}\overline{Rating}_{ST_{ji}}}{SP_{ST_i}} \quad (11)$$

where, $\overline{Rating}_{ST_{ji}}$ represents mean of the feedback rating provided by j^{th} patient for i^{th} team member. SP_{ST_i} and n are the number of surgical patients treated by the i^{th} team member and the total number of team members, respectively. Thus, the overall objective is to find surgical teams with a lower complication ratio and higher feedback rating.

Because the definition of charge in the conventional AEFA was not found to be suitable for solving MOOPs [25], thus this study uses multi-objective function given by SPEA2 [36] as the fitness function of the AEFA.

$$Fitness\,(ST_i) = Raw\_Fitness\,(ST_i) + Density\,(ST_i)$$

$$Raw_{Fitness(ST_i)} = \sum_{j\in \mathrm{POP}_{\mathrm{S}_t}\mathrm{UPOP}_{ext\,t}} dom\,(j)\,, \quad \text{where } dom\,(j)\,|\{i|i \in \mathrm{POP}_{\mathrm{S}_t}\mathrm{UPOP}_{\mathrm{ext}\,i}\}|$$

where, $Fitness\,(ST_i)$, $Density\,(ST_i)$, and $Raw\_Fitness\,(ST_i)$ represent the fitness value, additional density value, and raw fitness value of the i^{th} surgical team, respectively. For each surgical team,$Raw\_Fitness\,(ST_i)$ is computed in terms of $\mathrm{Comp}_t\,(ST)$ and $SF_t\,(ST)$, and it exhibits the strength of a solution (surgical team) by computing the number of other solutions on which it dominates and assigns a rank to the solution. In a situation where multiple solutions are non-dominant and are assigned similar ranks, the additional density value ($Density$) is used to differentiate various solutions. In this paper, k^{th} nearest neighbor algorithm is used to estimate the density.

5 Experimental Results and Discussion

Experiments were performed using a real case study of a multispecialty hospital in India. The proposed framework was implemented using a postoperative surgical dataset (POS) [33], which was obtained from the orthopedic surgery department of the hospital. Sub-section 5.1 discusses the performance of the SHM module. Subsection 5.2 discusses the performance of the STS module. Performances of the SHM and STS modules are discussed in sub-sections 5.1 and 5.2 respectively. Tab. 2 lists symbols used in the proposed framework.

Table 2: Symbols used in the proposed framework

Symbol	Definition	Symbol	Definition
P_{SSize}	Size of the initial search population	SF_t	Surgical feedback rating
P_{Search}	Search population	$\overline{Rating}_{ST_{ji}}$	Mean of surgical feedback ratings provided by the j^{th} patient of the i^{th} team member
P_{ESize}	Size of the external population size	SP_{ST_i}	The total number of surgical patients treated by the i^{th} surgical team
$P_{External}$	External population	$CompF_t$	Combination of the complication ratio ($Comp_t$) and the no-complication ratio ($noComp_t$)
QP_i	Position of the i^{th} charged particle (candidate solution)	$Fitness\,(ST_i)$	Fitness of the i^{th} surgical team
CLC_{max}	Maximum number of cluster centroids	$Density\,(ST_i)$	Additional density value of the i^{th} surgical team
THV_{SL}	Selection threshold value	$Raw_{Fitness}\,(ST_i)$	The raw fitness value of the i^{th} surgical team
CLC_{active}	Number of active cluster centroids	$Mean_g$	It represents the average distance to other data points in the same cluster
ϑ	Distance between data points and cluster centroids	$Mean_h$	It represents the average distance to the data points of different clusters.
P_{it}^{r}	t^{th} numeric attribute value of P_i	T_{COV}	Cutoff threshold value
P_{it}^{c}	t^{th} categorical attribute value of P_i	$MaxIT$	Maximum number of iterations
D	Objective space dimension	$TEAF_i^D$	Total electrostatic attraction force on a i^{th} charged particle in the D^{th} dimension.
P_{Comb}	Number of possible combinations of the surgical team	$a_i^D\,(T)$	Acceleration of a i^{th} charged particle in the D^{th} dimension
vel_i^D	Velocity of a i^{th} charged particle in the D^{th} dimension	q_i	Charge on a i^{th} charged particle

5.1 Performance Evaluation of the SHM Module

The performance of the SHM module was evaluated in three steps. Firstly, the performance of the proposed clustering algorithm was measured using nine real-life datasets (Tab. 3). Secondly, it was compared with six existing clustering for non-mixed dataset: (i) PSO, (ii) hybrid atom search optimization (ASO) and PSO (ASOPSO), (iii) ASO, (iv) hybrid PSO and gravitational search algorithm (PSOGSA), (v) hybrid PSO and firefly algorithm (PSOFA), (vi) hybrid ASO and sine-cosine algorithm (ASOSCA) [37]. The results revealed that the proposed clustering algorithm outperformed existing algorithms (Tab. 4). Subsequently, the performance of the proposed clustering algorithm was also compared with five existing clustering algorithms for mixed dataset: (i) k-means clustering algorithm, (ii) KHMCMD, (iii) k-prototypes clustering algorithm [38], (iv) Improved k-prototypes clustering algorithm [39], (v) algorithm proposed by Ji et al. [40]. The comparative results are shown in Tab. 5. Thirdly, the performance of the proposed clustering algorithm was evaluated using the POS dataset. The results revealed that considering all iterations, six active patient clusters with a selection frequency of 1.6, an average fitness of 0.96, and a standard deviation of 0.13 were selected as an optimal solution (Tab. 6).

Table 3: Characteristics of real-life datasets

Dataset	Data points	Attributes			Classes
		Numeric	Categorical	Others	
Breast tissue	106	9	–	–	6
CMC	1473	2	4	3	2
Wine	178	13	–	–	3
Iris	150	4	–	3	3
Ecoli	336	7	–	–	8
Heart disease (1)	303	5	8	–	2
Heart disease (2)	270	6	8	–	5
Credit approval	690	6	8	–	2
Soybean	47	–	35	–	4

Table 4: Comparison of the performance of proposed and existing clustering algorithms for non-mixed dataset

Dataset	Index	Algorithm						
		PSO	ASOPSO	ASO	PSOGSA	PSOFA	ASOSCA	Proposed algorithm
Breast tissue	Silhouette index	0.74	0.71	0.29	0.77	0.69	0.77	0.82
	Dunn index	0.43	0.26	0.17	0.52	0.31	0.66	0.71
	Davies-Bouldin index	0.61	0.51	1.07	0.57	0.56	0.63	0.44
CMC	Silhouette index	0.25	0.17	0.20	0.21	0.22	0.247	0.38
	Dunn index	0.08	0.07	0.06	0.10	0.09	0.04	0.12
	Davies-Bouldin index	0.61	0.78	0.61	0.61	0.68	0.31	0.30
Wine	Silhouette index	0.29	0.32	0.23	0.36	0.37	0.52	0.55
	Dunn index	0.07	0.06	0.05	0.08	0.07	0.12	0.14
	Davies-Bouldin index	0.52	0.56	0.60	0.41	0.43	0.12	0.12
Ecoli	Silhouette index	0.001	0.06	0.13	0.05	0.00	0.19	0.20
	Dunn index	0.05	0.06	0.07	0.06	0.06	0.11	0.12
	Davies-Bouldin index	0.69	0.80	0.82	0.72	0.7	0.76	0.51

(∼ shows results not available)

Table 5: Comparison of the performance of proposed and existing clustering algorithms for mixed dataset

Dataset	Proposed algorithm	Improved k-prototypes	k-prototypes	KHMCMD	KMCMD	Ji et al. [40]
	AC (STD)	AC (STD)	AC (STD)	AC (STD)	AC (STD)	AC (STD)
Heart disease (1)	0.853 (±0.13)	0.826 (∼)	0.577 (∼)	0.840 (±0.15)	0.838 (±0.15)	0.853 (±0.13)
Heart disease (2)	0.830 (±0.19)	0.653 (∼)	0.546 (∼)	0.816 (±0.33)	0.807 (±1.20)	0.830 (±0.19)
Credit approval	0.864 (±0.11)	0.779 (∼)	0.562 (∼)	0.852 (±0.38)	0.822 (±12.77)	0.864 (±0.11)
Iris	0.95 (±0.17)	0.822 (∼)	0.819 (∼)	∼	∼	0.95 (±0.17)
Soybean	0.93 (±0.17)	0.90 (∼)	0.856 (∼)	∼	∼	0.93 (±0.17)

AC: Average accuracy, STD: Standard deviation. (∼ shows results not available)

Table 6: Performance evaluation of the proposed clustering algorithm on the POS dataset

Number of active clusters selected	Parameters	Iterations				
		1–10	11–20	21–30	31–40	41–50
2	Selection frequency	0.0	0.3	0.0	0.5	0.0
	Average fitness	0.0	0.70 (±0.42)	0.0	0.52 (±0.33)	0.0
3	Selection frequency	0.4	0.3	0.4	0.0	0.6
	Average fitness	0.74 (±0.56)	0.71 (±0.52)	0.58 (±0.61)	0.0	0.66 (±0.25)
4	Selection frequency	0.6	0.8	0.4	0.6	0.6
	Average fitness	0.65 (±0.40)	0.83 (±0.34)	0.76 (±0.39)	0.80 (±0.36)	0.52 (±0.64)
5	Selection frequency	0.3	0.7	0.6	0.8	1.0
	Average fitness	0.36 (±0.47)	0.60 (±0.36)	0.69 (±0.23)	0.55 (±0.37)	0.91 (±0.22)
6	Selection frequency	1.0	0.8	1.2	**1.6**	0.4
	Average fitness	0.62 (±0.16)	0.74 (±0.35)	0.92 (±0.18)	**0.96 (±0.13)**	0.50 (±0.32)
7	Selection Frequency	0.4	0.7	0.5	0.5	0.4
	Average Fitness	0.57 (±0.58)	0.67 (±0.40)	0.30 (±0.28)	0.40 (±0.40)	0.52 (±0.59)
8	Selection frequency	0.3	0.1	0.3	0.0	0.0
	Average fitness	0.53 (±0.32)	0.22 (±0.38)	0.50 (±0.41)	0.0	0.0

5.2 Performance Evaluation of the STS Module

The performance of the STS module of the proposed MOOA is evaluated on the basis of parameters listed in Tab. 7 using three benchmark functions, namely SCH, FON, and ZDT1 [41]. Subsequently, the performance of the proposed MOOA was compared with four existing MOOAs: SPGSA [31], NSGA II [41], NSPSO [42], and BCMOA [43], on the basis of three performance parameters, namely converge metric [CM], diversity metric [DM] [41], and generational distance metric (GD) [44]. A minimum value of all these parameters is desired for optimal solutions. The results demonstrated that the proposed algorithm achieved a minimum value for CM, DM, and GD (in terms of the mean) for all considered benchmark functions (Tab. 8). This finding indicated that the proposed algorithm outperformed existing MOOAs in terms of the convergence rate while maintaining the diversity among optimal solutions. The results shown in Tab. 8 are presented as a graph in Fig. 2. For better representation, results in the graphs are shown using a logarithmic scale, where higher logarithmic value represents minimum value of the mean. As shown in Fig. 2, the proposed algorithm achieved a high logarithmic value of the mean (minimum value of the mean) for all metrics, indicating that the proposed algorithm is more efficient and robust in comparison to existing MOOAs.

Table 7: Parameters used in the proposed multi-objective optimization algorithm

Description	Parameter	Value for benchmark functions	Value for surgical team selection
Population (Surgical team) size	P_{SSize}	100	135
External population size	P_{ESize}	100 for SCH, FON, and ZDT1	6
Initial value of Coulomb's constant	K_0	500	500
The maximum number of iterations	$MaxIT$	100 for SCH and FON, and 250 for ZDT1	50
Initial, Final crossover probability	P_{CR}, P_{CF}	1.0, 0.0	1.0, 0.0
Initial, Final mutation probability	P_{MI}, P_{MF}	0.01, 0.001	0.01, 0.001

Table 8: Comparison of the performance of proposed and existing multi-objective optimization algorithms

Performance metric	Benchmark functions		Algorithm				
			Proposed algorithm	SPGSA	NSGA II	NSPSO	BCMOA
CM Metric	SCH	Mean	1.59×10^{-1}	1.65×10^{-1}	3.8×10^{-1}	8.6×10^{-1}	7.60×10^{-1}
	FON	Mean	1.58×10^{-1}	1.61×10^{-1}	4.14×10^{-1}	5.81×10^{-1}	4.8×10^{-1}
	ZDT1	Mean	1.56×10^{-1}	1.61×10^{-1}	4.06×10^{-1}	6.38×10^{-1}	5.9×10^{-1}
DM Metric	SCH	Mean	2.81×10^{-3}	3.2×10^{-3}	3.14×10^{-3}	3.40×10^{-1}	3.2×10^{-3}
	FON	Mean	1.68×10^{-3}	1.7×10^{-3}	2.36×10^{-3}	2.84×10^{-1}	2.7×10^{-3}
	ZDT1	Mean	1.09×10^{-3}	1.1×10^{-3}	4.02×10^{-3}	3.81×10^{-1}	1.1×10^{-3}
GD Metric	SCH	Mean	3.19×10^{-4}	3.78×10^{-4}	3.68×10^{-4}	4.5×10^{-4}	3.78×10^{-4}
	FON	Mean	3.65×10^{-5}	2.13×10^{-4}	2.94×10^{-4}	3.6×10^{-4}	3.62×10^{-4}
	ZDT1	Mean	3.02×10^{-5}	2.4×10^{-4}	5.56×10^{-4}	4.3×10^{-4}	2.02×10^{-4}

(∼ shows results not available)

The details related to a surgical patient (Tab. 9) were submitted as input to the STS module. Then, a suitable active patient cluster was selected from the six optimal active patient clusters (obtained from the SHM module), and associated surgical teams were extracted from it.

The selected cluster contained 400 orthopedic surgical records in which 15 distinct surgeons, 40 anesthesiologists, and 30 nurses were involved. It resulted in 18000 possible combinations of surgical teams. Finally, 135 surgical teams were generated as an initial search population, and the proposed algorithm was implemented on it. The results are shown in Figs. 3 and 4. Figs. 3a and 3b show the comparison between the proposed and existing algorithms in terms of the complication ratio and surgical feedback rating, respectively. From Fig. 3a it is clear that the proposed algorithm converged faster to the optimal solution and obtained the lowest value of the complication ratio in comparison to existing algorithms. Similarly, Fig. 3b illustrates that the proposed algorithm achieved maximum value of surgical feedback rating also. The final results presented in Fig. 4 revealed that six optimal surgical teams were selected for the referred surgical patient. This can be assigned to the patient as per availability of the team members.

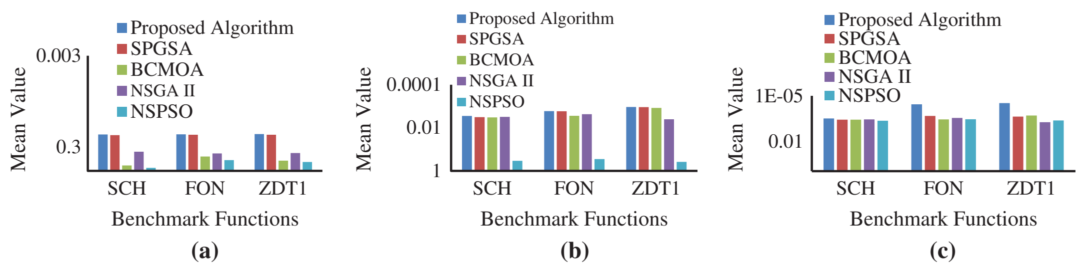

Figure 2: Comparison of performance between proposed and existing MOOAs based on (a) CM, (b) DM, and (c) GD

Table 9: Attributes of a surgical patient

Attribute	Type	Description
Age	Numeric	62
Gender	Categorical	Male
BMI	Numeric	42
ASA fitness grade	Numeric	2
Marital Status	Categorical	Married
Ethnicity	Categorical	Indian
Comorbidity	Numeric	3
Type of Surgery	Categorical	Minor
Surgery Duration	Numeric	Length of surgical procedure
Procedural code	Categorical	0KQV0ZZ
Diagnose code	Categorical	S82.91XA
Surgery Domain	Categorical	Orthopedic
Grade of Surgery	Categorical	Mild
Urgency of surgery	Categorical	Elective
LOS	Numeric	3.4 days

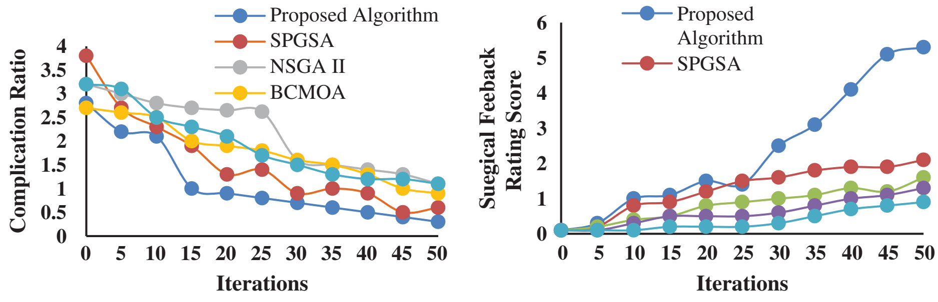

Figure 3: Comparison of performance between proposed and existing MOOAs for surgical team selection based on (a) complication ratio and (b) surgical feedback rating score

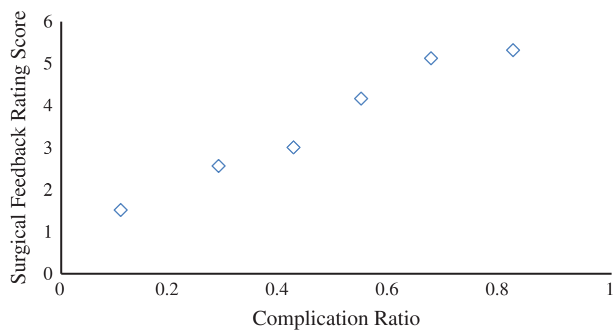

Figure 4: Optimal Pareto list of the selected surgical team

6 Conclusion

High-quality surgical services are essential from the perspective of hospitals and patients both. Surgical outcomes depend on the performance of dedicated surgical teams, which in turn affects hospital's efficiency and patients' trust towards that hospital. In multispecialty hospitals many surgical patients are treated concurrently. Therefore, arranging a suitable surgical team for achieving success of a surgical procedure is crucial and challenging. This study addresses the challenge of selection of an optimal list of surgical teams for a referred patient, so that each patient can receive high-quality surgical care. In this paper a framework is proposed to assist decision makers in selecting an optimal list of surgical teams. The proposed framework contains two modules: SHM and STS. SHM focuses on arranging existing surgical patients into optimal patient subgroups. This arrangement of patients further assists the STS module in selecting the optimal list of surgical teams. In this paper, an efficient clustering algorithm for mixed data is proposed to identify optimal subgroups of patients. Besides, a MOOA is proposed to select optimal surgical teams. The proposed framework is validated through a case study of the orthopedic surgery department at a multispecialty hospital in India. Data related to existing surgical records is obtained from the hospital. The performance of the proposed algorithms is evaluated based on different benchmark functions and datasets, and is compared with the existing algorithms also. The experimental evaluation revealed that the proposed algorithm yielded more favorable and significant results in comparison to the existing algorithms, indicating the efficient functionality of the proposed framework.

Funding Statement: The authors received no specific funding for this study.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

References

[1] A. Jones, "Multidisciplinary team working: Collaboration and conflict," *International Journal of Mental Health Nursing*, vol. 15, no. 2, pp. 19–28, 2006.

[2] R. Guimera, B. Uzzi, J. Spiro and L. A. N. Amaral, "Team assembly mechanisms determine collaboration network structure and team performance," *Science*, vol. 308, no. 5722, pp. 697–702, 2005.

[3] Y. Y. Hu, A. F. Arriaga, E. M. Roth, S. E. Peyre, K. A. Corso *et al.,* "Protecting patients from an unsafe system: The etiology & recovery of intra-operative deviations in care," *Annals of Surgery*, vol. 256, no. 2, pp. 203–210, 2012.

[4] K. Mazzocco, D. B. Petitti, K. T. Fong, D. Bonacum, J. Brookey *et al.,* "Surgical team behaviors and patient outcomes," *American Journal of Surgery*, vol. 197, no. 5, pp. 678–685, 2009.

[5] A. Ebadi, P. J. Tighe, L. Zhang and P. Rashidi, "DisTeam: A decision support tool for surgical team selection," *Artificial Intelligence in Medicine*, vol. 76, no. 50, pp. 16–26, 2017.

[6] S. E. Regenbogen, C. C. Greenberg, D. M. Studdert, S. R. Lipsitz, M. J. Zinner *et al.,* "Patterns of technical error among surgical malpractice claims: An analysis of strategies to prevent injury to surgical patients," *Annals of surgery*, vol. 246, no. 5, pp. 705–711, 2007.

[7] L. L. Faltz, J. N. Morley, E. Flink and P. D. Dameron, "The New York model: Root cause analysis driving patient safety initiative to ensure correct surgical and invasive procedures," in *Advances in Patient Safety: New Directions and Alternative Approaches (Vol. 1: Assessment)*. Rockville (MD), USA: Agency for Healthcare Research and Quality, 2008.

[8] C. K. Christian, M. L. Gustafson, E. M. Roth, T. B. Sheridan, T. K. Gandhi *et al.,* "A prospective study of patient safety in the operating room," *Surgery*, vol. 139, no. 2, pp. 159–173, 2006.

[9] S. Guerlain, R. B. Adams, F. B. Turrentine, T. Shin, H. Guo *et al.,* "Assessing team performance in the operating room: Development and use of a "black-box" recorder and other tools for the intraoperative environment," *Journal of the American College of Surgeons*, vol. 200, no. 1, pp. 29–37, 2005.

[10] S. K. Howard, D. M. Gaba, K. J. Fish, G. Yang and F. H. Sarnquist, "Anesthesia crisis resource management training: Teaching anesthesiologists to handle critical incidents," *Aviation, Space, and Environmental Medicine*, vol. 63, no. 9, pp. 763–770, 1992.

[11] L. S. Leach, R. C. Myrtle, F. A. Weaver and S. Dasu, "Assessing the performance of surgical teams," *Health care management review*, vol. 34, no. 1, pp. 29–41, 2009.

[12] L. S. Franz and J. L. Miller, "Scheduling medical residents to rotations: Solving the large-scale multiperiod staff assignment problem," *Operations Research*, vol. 41, no. 2, pp. 269–279, 1993.

[13] P. Finamore, M. Spruit, J. Schols, R. A. Incalzi, E. F. Wouters *et al.,* "Clustering of patients with end-stage chronic diseases by symptoms: A new approach to identify health needs," *Aging Clinical and Experimental Research*, vol. 62, no. 62, pp. 1–11, 2020.

[14] D. Gamberger, B. Ženko, A. Mitelpunkt, N. Shachar and N. Lavrač, "Clusters of male and female Alzheimer's disease patients in the Alzheimer's Disease Neuroimaging Initiative (ADNI) database," *Brain Informatics*, vol. 3, no. 3, pp. 169–179, 2016.

[15] H. Petwal and R. Rani, "Prioritizing the surgical waiting list-cosine consistency index: An optimized framework for prioritizing surgical waiting list," *Journal of Medical Imaging and Health Informatics*, vol. 10, no. 12, pp. 2876–2892, 2020.

[16] S. R. Newcomer, J. F. Steiner and E. A. Bayliss, "Identifying subgroups of complex patients with cluster analysis," *American Journal of Managed Care*, vol. 17, no. 8, pp. e324–32, 2011.

[17] Y. Li, B. Rosenfeld, H. Pessin and W. Breitbart, "Bayesian nonparametric clustering of patients with advanced cancer on anxiety and depression," in *IEEE Int. Conf. on Machine Learning and Applications*, Cancun, Mexico, pp. 674–678, 2017.

[18] C. Yu, B. T. Baune, K. A. Fu, M. L. Wong and J. Licinio, “Genetic clustering of depressed patients and normal controls based on single-nucleotide variant proportion,” *Journal of Affective Disorders*, vol. 227, no. 17, pp. 450–454, 2018.
[19] S. Karthikeyan and T. Christopher, “A hybrid clustering approach using artificial bee colony (ABC) and particle swarm optimization,” *International Journal of Computer Applications*, vol. 100, no. 15, pp. 1–6, 2014.
[20] A. Ahmad and L. Dey, “A K-mean clustering algorithm for mixed numeric and categorical data,” *Data & Knowledge Engineering*, vol. 63, no. 2, pp. 503–527, 2007.
[21] A. Ahmad and S. Hashmi, “K-Harmonic means type clustering algorithm for mixed datasets,” *Applied Soft Computing*, vol. 48, pp. 39–49, 2016.
[22] V. Kumar and D. Kumar, “Automatic clustering and feature selection using gravitational search algorithm and its application to microarray data analysis,” *Neural Computing and Applications*, vol. 31, no. 8, pp. 3647–3663, 2019.
[23] V. Kumar, J. K. Chhabra and D. Kumar, “Automatic data clustering using parameter adaptive harmony search algorithm and its application to image segmentation,” *Journal of Intelligent Systems*, vol. 25, no. 4, pp. 595–610, 2016.
[24] S. Das, A. Abraham and A. Konar, “Automatic hard clustering using improved differential evolution algorithm,” in *Metaheuristic Clustering*. Vol. 178. Berlin, Heidelberg: Springer, pp. 137–174, 2009.
[25] A. Yadav, “AEFA: Artificial electric field algorithm for global optimization,” *Swarm and Evolutionary Computation*, vol. 48, no. 1, pp. 93–108, 2019.
[26] A. Y. Hamed, M. H. Alkinani and M. R. Hassan, “A genetic algorithm to solve capacity assignment problem in a flow network,” *Computers, Materials & Continua*, vol. 64, no. 3, pp. 1579–1586, 2020.
[27] W. Liu, Y. Tang, F. Yang, Y. Dou and J. Wang, “A multi-objective decision-making approach for the optimal location of electric vehicle charging facilities,” *Computers, Materials & Continua*, vol. 60, no. 2, pp. 813–834, 2019.
[28] N. Srinivas and K. Deb, “Muiltiobjective optimization using nondominated sorting in genetic algorithms,” *Evolutionary Computation*, vol. 2, no. 3, pp. 221–248, 1994.
[29] F. Gu, H. L. Liu and K. C. Tan, “A multi-objective evolutionary algorithm using dynamic weight design method,” *International Journal of Innovative Computing, Information and Control*, vol. 8, no. 5(B), pp. 3677–3688, 2012.
[30] H. R. Hassanzadeh and M. Rouhani, “A multi-objective gravitational search algorithm,” in *IEEE Int. Conf. on Computational Intelligence, Communication Systems and Networks*, Liverpool, UK, pp. 7–12, 2010.
[31] X. Yuan, Z. Chen, Y. Yuan, Y. Huang and X. Zhang, “A strength pareto gravitational search algorithm for multi-objective optimization problems,” *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 29, no. 6, pp. 1–39, 2015.
[32] H. Nobahari, M. Nikusokhan and P. Siarry, “Non-dominated sorting gravitational search algorithm,” in *Int. Conf. on Swarm Intelligence*, Cergy, France, pp. 1–10, 2011.
[33] H. Petwal and R. Rani, “An efficient clustering algorithm for mixed dataset of postoperative surgical records,” *International Journal of Computational Intelligence Systems*, vol. 13, no. 1, pp. 757–770, 2020.
[34] M. Thakur, S. S. Meghwani and H. Jalota, “A modified real coded genetic algorithm for constrained optimization,” *Applied Mathematics and Computation*, vol. 235, no. 3, pp. 292–317, 2014.
[35] Y. Liu, B. Niu and Y. Luo, “Hybrid learning particle swarm optimizer with genetic disturbance,” *Neurocomputing*, vol. 151, no. 3, pp. 1237–1247, 2015.
[36] E. Zitzler, M. Laumanns and L. Thiele, “SPEA2: Improving the strength Pareto evolutionary algorithm,” *TIK-report*, vol. 103, pp. 1–19, 2001.
[37] M. A. Elaziz, N. Nabil, A. A. Ewees and S. Lu, “Automatic data clustering based on hybrid atom search optimization and sine-cosine algorithm,” in *IEEE Congress on Evolutionary Computation*, Wellington, New Zealand, pp. 2315–2322, 2019.

[38] Z. Huang, "Clustering large data sets with mixed numeric and categorical values," in *First Pacific-Asia Conf. on Knowledge Discovery and Data Mining*, Singapore, pp. 21–34, 1997.

[39] J. Ji, T. Bai, C. Zhou, C. Ma and Z. Wang, "An improved k-prototypes clustering algorithm for mixed numeric and categorical data," *Neurocomputing*, vol. 120, no. 1, pp. 590–596, 2013.

[40] J. Ji, W. Pang, Y. Zheng, Y. Z.Wang and Z. Ma, "An initialization method for clustering mixed numeric and categorical data based on the density and distance," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 29, no. 7, pp. 1–16, 2015.

[41] K. Deb, A. Pratap, S. Agarwal and T. A. Meyarivan, "A fast and elitist multi-objective genetic algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, 2002.

[42] X. Li, "A non-dominated sorting particle swarm optimizer for multi-objective optimization," in *Genetic and Evolutionary Computation Conf.*, Berlin, Heidelberg, Springer, pp. 37–48, 2003.

[43] M. A. Guzmán, A. Delgado and J. De Carvalho, "A novel multi-objective optimization algorithm based on bacterial chemotaxis," *Engineering Applications of Artificial Intelligence*, vol. 23, no. 3, pp. 292–301, 2010.

[44] D. A. Van Veldhuizen and G. B. Lamont, "On measuring multi-objective evolutionary algorithm performance," in *Congress on Evolutionary Computation*. La Jolla, CA, USA, 204–211, 2000.