

<sup>1</sup>Zhong Wu<sup>2</sup>Shuang Wang\*

# Optimization of Seating Arrangement in Sports Competition Venues Based on Recurrent Graph Neural Network



**Abstract:** - Seating in sports venues is a type of seating where rows are much more frequent than in other types of auditorium seating. Traditional seating looks to maximize capacity over fan experience. The stadium experience can be enhanced by recommending appropriate seating by viewer's preferences and past behavior. Group customers would want to sit together when they go to a sports arena, but sometimes there are not enough seats available together. This study's methodology for improving viewing experience by optimizing seating arrangement using game type, historical ticket sales and opponent team is offered in this study as a way to get around this drawback. The data are collected from Los Angeles Memorial Sports Arena seating dataset. Afterward, the data are fed to pre-processing. In pre-processing segment, the noise is removed and data is enhanced using Adaptive Robust Cubature Kalman Filter (ARCKF). The outcome from the pre-processing data is transferred to the Recurrent Graph Neural Network (RecGNN). The reserved seating, bowl seating and stadium seating are successfully classified by using RecGNN. RecGNN's weight parameter is optimized by the Lotus Effect Optimization Algorithm (LEA). On the Python working platform, the proposed RecGNN-LEA is implemented. The proposed strategy is analyzed using performance measures including recall, f1-score, accuracy, precision, and computation time. RecGNN's weight parameter is optimized by the Lotus Effect Optimization Algorithm (LEA). On the Python working platform, the proposed RecGNN-LEA is implemented. The proposed method is analyzed using performance measures including recall, f1-score, accuracy, precision, and computation time. The gained results of the proposed RecGNN-LEA method attains higher accuracy of 16.61%, 18.89%, and 17.92%, higher sensitivity of 16.37%, 12.23%, and 18.56% and higher precision of 14.81%, 16.79%, and 18.23%. The proposed SASCV-RecGNN-LEA method is compared with the existing methods such as SASCV-CNN, SASCV-LaRSA, and SASCV-TDNN models respectively.

**Keywords:** Seating Arrangement, Lotus Effect Optimization Algorithm, Adaptive Robust Cubature Kalman Filter, Recurrent Graph Neural Network, Sports.

## I. INTRODUCTION

Many websites, such as Stubhub or Ticketmaster, provide reserved seating for events, including sporting events and other entertainment [1]. Customers agree to situate themselves near strangers when they purchase a ticket, necessitating a locational decision [2, 3]. These decisions reflect both typical and difficult human situations, and they have a significant impact on the final consumer experience [4]. As a result, ticket-selling platforms provide an intriguing potential for recommender systems, which may be capable of enhance event-level occupancy in addition to suggesting seats that prospective buyers will find appealing across a range of reserved-seating locations [5, 6]. Seats symbolize classrooms, and half-filled rooms serve as input [7]. This allows data to be utilized to model higher-order interactions, but as the data is aggregated, common preferences will mask latent heterogeneity, reducing prediction performance from aggregate data [8, 9].

Customers can optimize their unique location preferences with reserved seating systems, which also probably benefit the provider [10, 11]. Group visitors usually want to sit next to each other, however occasionally there aren't enough seats for everyone in the group to enter the sports centre [12]. Using operations research to intelligently distribute seats to patrons is the best way for sports centers to maximize their revenue [13]. The spending habits of individual consumers as well as groups of customers consisting of more than two people should be taken into account when allocating seats to customers [14, 15]. Discrete choice models or recommendation systems can be used to model the data of each unique client [16]. By doing this, variations in preferences at the individual level can be captured. However, insufficient customer data also tends to negatively impact individual-level modeling performance [17, 18].

The neural network receives input from the stochastic model, which simulates 150,000 seating configurations [19]. While the other, learning-independent portion of these simulated events is used for testing, the majority of them are used to train our SASCV-RecGNN-LEA model. The competitive balance is evaluated for feasibility using seat occupancy rates. It also looks into a few physical attendance criteria, for example, the effect of the home team's tenacity. The algorithm obtains optimal configurations in seating instances in a matter of seconds. The seating arrangement model SASCV-RecGNN-LEA is analyzed from multiple aspects like accuracy, f1-score, precision, recall and computation time.

<sup>1</sup> Associate Professor, Physical Education School, Wuhan Business University, Wuhan, Hubei, 430056, China

<sup>2</sup> Associate Professor, School of Railway Transportation Management and Logistics, Wuhan Railway Vocational College of Technology, Wuhan, Hubei, 430205, China. wangsshuai@163.com

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Major input to the work that is compiled here;

- At first, the data is gathered via the Los Angeles Memorial Sports Arena seating dataset.
- Using Adaptive Robust Cubature Kalman Filtering the noise is removed and data is enhanced in the pre-processing segment.
- The pre-processed data are fed into the Recurrent Graph Neural Network in order to effectively categorize the seating arrangement into reserved seating, bowl seating and stadium seating.
- The proposed RecGNN-LEA approach is implemented, and performance metrics such as computation time, accuracy, precision, recall, and F1-score are examined.

The remaining portions of this manuscript are organized as: sector 2 examines a survey of the literature; Sector 3 describes the proposed technique; Sector 4 gives the findings and discussion; and Sector 5 concludes.

## II. LITERATURE REVIEW

Many research works were indicated in the literature relating to the seating arrangement in sports venues; a few recent works were reviewed here,

Moins et al. [20] have suggested that predicting locational choices, or where people choose to sit, was a difficult challenge due to the great heterogeneity of preferences, which depend on other factors in addition to the location of the seats in the surroundings. The technique employed CNNs to capture higher-order interactions between available seat attributes and individual-level discrete choice models. Taking into consideration complex real-world locational choice data, such as modifications to ticket purchases and transaction numbers and locations from the past, the system showed flexibility. Utilizing information from a well-known North American music venue's ticket sales and locational choice experiment data, it was consistently demonstrated that adding a CNN to individual-level discrete choice models improves prediction accuracy.

Kwag et al. [21] have suggested that the revenue per person tends to increase with the amount of customers in a group. Following data analysis to identify revenue and client stay times, operations research was employed to develop the best seat allocation plan. Because each client group earns different amounts of income over time, smaller groups of customers can be prioritized in the same way as larger groups, according to a numerical experiment conducted using real data. Furthermore, the opportunity cost of turning away customers who could have filled seats to accommodate larger groups of customers who make more money at alternative timeslots was considered.

Schultz and Reitmann [22] have suggested that timely air traffic movements depended on dependable and consistent ground operations. Variations in aircraft ground operations have a greater impact on flight timeliness than do uncertainties in the airborne period. Recurrent neural networks may anticipate the outcome of a running boarding event. The Long Short-Term Memory model was used and trained extensively. Data on aircraft boarding occurrences were provided in the absence of operational data pertaining to the specific passenger behavior, using a reliable and tested boarding simulation environment.

Blanchard et al. [23] have suggested that a method of measuring consumer preference for positioning oneself in relation to others during consuming activities, such as purchasing tickets for reserved seats at a show. This technique demonstrates how consumers' preferences for proximity to focal points and other consumers differ. It recommends that event organizers collect information beyond buy ticket logs, including individuals who did not purchase. More than 2,000 people participated in the locational choice studies, which replicated reserved seating arrangements.

Nehyba et al. [24] have suggested that examine the level of contact between university students and the seating configuration in the groups of pre-service instructors during the reflective practice. Examine the variations among the different fields of study as well as the facilitator's impact on the exchange. 58 students in 4 distinct subject areas underwent a total of 153 repeat assessments with a counterbalanced design, with a total of 4 assessments in each group.

Sung et al. [25] have suggested that they look for variables that affect how fans in Korean professional baseball league get involved for long-term growth. It examines the uncertainty-of-outcome theory by examining how competitive balance (CB) affects stadium seat occupancy. Examined 2160 games' worth of data from the Korea Baseball Organization's (KBO) archives over three years (2015–2017). The home team's CB has an impact on the team's seat occupancy rate (SOR), as does the entire squad. Additionally, it was demonstrated that CB and SOR had an inverted U-shaped curvilinear relationship. On the other hand, the host team's league-wide winning percentage significantly affected the SOR.

Bergman [26] has suggested that over the past century, numerous generalizations of knapsack issues have been researched, making them a crucial component of the operations research literature. The quadratic multiknapsack problem (QMKP) has garnered attention recently. There were several heuristics available, but no precise techniques for the QMKP have been documented in the literature. For the QMKP, it provides an exact branch-and-price algorithm. It was demonstrated that an optimization model for table event seating was strongly associated with the QMKP, and computational testing suggests that the approach was especially appropriate for this use case.

*A. Motivation*

A general overview of current research indicates that seating arrangements have a significant impact on spectators' or customers' viewing experiences. Group customers would want to sit together when they go to a sports arena, but sometimes there were not enough seats available together. Many researchers deal that problem with the different technologies like Convolutional Neural Network (CNN), Lyko and Rudek's Search Algorithm (LaRSA) and Time Delay Neural Network (TDNN). The CNN can record higher order relationships between the attributes of the open seats. Due to its flexibility, the framework can handle the complexity of locational choice data found in the real world. LaRSA could derive unbiased outcomes by taking into account every scenario involving seat allotment. TDNN is the most suitable approach to encapsulate the fundamental concept of finding correlations and long-term relationships between the complexity metric's components. There aren't many approach-based publications in the literature that address this issue; these shortcomings and issues were what inspired the research project.

III. PROPOSED METHODOLOGY

In this section, Optimization of Seating Arrangement in Sports Competition Venues Based on Recurrent Graph Neural Network using a hybrid method is discussed. This work presents a new approach for seating arrangement in sports venues based on the Los Angeles Memorial Sports Arena seating data. The block diagram that demonstrates the proposed approach is illustrated in Fig 1. It contains three stages like data collection, preprocessing and classification.

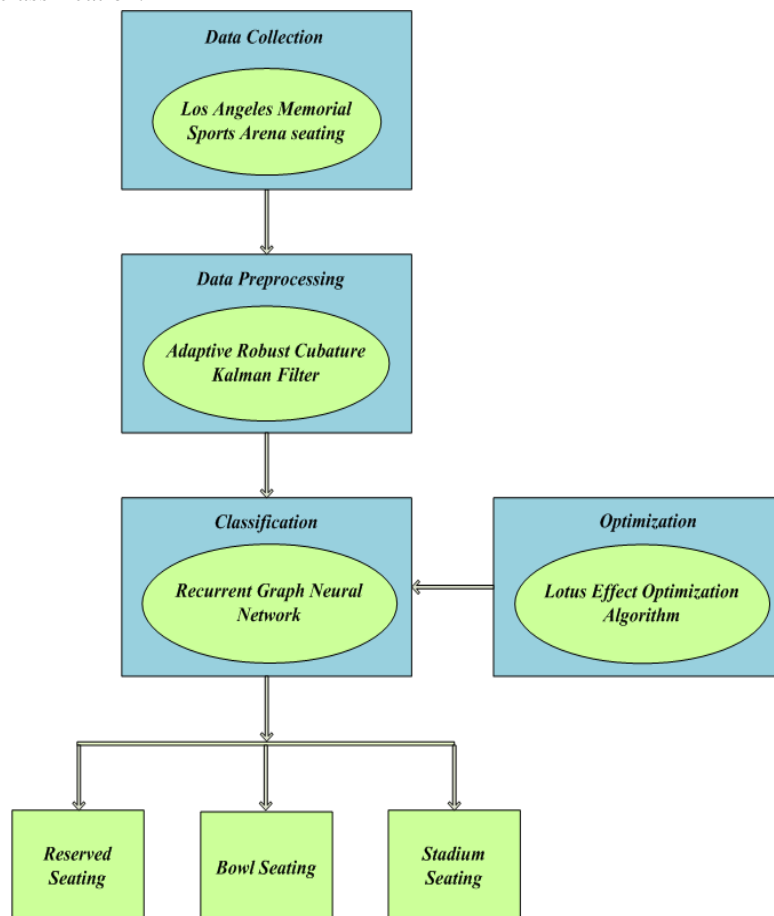


Fig 1: The block diagram that demonstrates the proposed approach

A. Data Acquisition

The data have been acquired from the Los Angeles Memorial Sports Arena seating dataset [27]. It shows seating arrangement for the delegates and viewers from 51 states and territories for a sports event.

B. Preprocessing using Adaptive Robust Cubature Kalman Filter (ARCKF)

This section proposes adaptive resilient cubature kalman filtering as a pre-processing method [28]. Before detailing the ARCKF algorithm, the pre-processing section reduces dynamics error using adaptive robust cubature kalman filtering. An ARCKF can filter out noise in systems and measurements while mitigating the negative effects of innovation and observation outliers. under modify the state estimation error covariance matrix under changing circumstances, an adaptive technique is applied.

The related state estimation error covariance matrix is fed into the cubature point generator, which generates cubature points that represent statistical features.

Officially, obtain

$$Y_{i,k-1} = \hat{y}_{k-1} + \xi_i \sqrt{\hat{Q}_{k-1}}, \quad i = 1, \dots, 2n \tag{1}$$

Here,  $Y_{i,k-1}$  is denoted as the  $i^{\text{th}}$  cubature point of  $\hat{y}_{k-1}$ ,  $n$  is denoted as the dimension of state variables,  $\sqrt{(\cdot)}$  is denoted as the Cholesky's decomposition process,  $\xi_i$  is denoted as the  $i$ th column in the fundamental data point collection.

The transition function between states is utilized to generate the cubature points. Next, the corresponding state error covariance and the anticipated state can be computed as

$$Y_{i,k}^* = f(Y_{i,k-1}, u_{k-1}), \tag{2}$$

$$i = 1, \dots, 2n$$

$$\tilde{y}_k = \frac{1}{2n} \sum_{i=1}^{2n} Y_{i,k}^* \tag{3}$$

$$\tilde{Q}_k = \frac{1}{2n} \sum_{i=1}^{2n} Y_{i,k}^* (Y_{i,k}^*)^T - \tilde{y}_k \tilde{y}_k^T + P_{k-1} \tag{4}$$

Where,  $Y_{i,k}^*$  is denoted as the transformed points of cubature,  $\tilde{y}_k$  is denoted as the forecasted state,  $\tilde{Q}_k$  is denoted as the related covariance of errors, the superscript  $T$  is denoted as the matrix transpose process.

The relationship among the true state and anticipated state is used to build the batch-mode regression form.

$$\tilde{y}_k = y_k - \eta_k \tag{5}$$

Where,  $\eta_k$  is denoted as the forecast error.

Furthermore, by using the measurement function and the arithmetic linearization technique, the following can be derived

$$x_k = H_k(y_k - \tilde{y}_k) + h(\tilde{y}_k) + v_k \tag{6}$$

Where,  $H_k(Q_{xy,k})^T (\tilde{Q}_k)^{-1}$  is denoted as the statistical regression matrix.

The compact form of the above both equations are given below:

$$\tilde{y}_k = \tilde{H}_k y_k + \tilde{e}_k \tag{7}$$

Where the following method can be used to calculate the covariance matrix  $\tilde{e}_k$  :

$$\sum_k = E[\tilde{e}_k \tilde{e}_k^T] = S_k S_k^T \tag{8}$$

Here,  $S_k$  also be calculated utilizing the Cholesky decomposition method or the UD factorization.

For the outlier detection and down-weight, the prediction state vector and the innovation vector must be established as follows to create a two-dimensional matrix.

$$Z_k = \begin{bmatrix} x_{k-1} - h(\tilde{y}_k - 1) & x_k - h(\tilde{y}_k) \\ \tilde{y}_k - 1 & \tilde{y}_k \end{bmatrix} \tag{9}$$

Here, the superscripts  $k$  and  $k - 1$  are denoted as the instants of time,  $x_{k-1} - h(\tilde{y}_k - 1)$  and  $x_k - h(\tilde{y}_k)$  are denoted as the innovation vector at the instants of time  $k - 1$  and  $k$ ,  $\tilde{y}_k - 1$  and  $\tilde{y}_k$  are denoted as the prediction state.

By applying the total influence function technique, an estimating error covariance matrix can be generated and changed in the following ways to improve the proposed method's resilience against outliers.

$$\tilde{Q}_k = \begin{cases} \tilde{Q}_k - K_k Q_{yy,k} K_k^T & \text{if } \max(PS_i) \leq \chi_{2,(.0975)}^2 \\ \mu(C_k^T C_k)^{-1} (C_k^T \Omega_{\sigma} C_k) (C_k^T C_k)^{-1}, & \text{otherwise} \end{cases} \quad (10)$$

Where,  $\tilde{Q}_k$  is denoted as the error matrix's state prediction covariance at any given instant in time,  $\chi_{2,(.)}^2$  is denoted as the chi-square distribution,  $\chi_{2,(.0975)}^2$  is denoted as the value of  $\chi_{2,(.)}^2$ ,  $Q_{yy,k}$  is denoted as the anticipated measurement's covariance matrix and  $K_k$  is denoted as the Kalman gain that is calculated as

$$Q_{yy,k} = \frac{1}{2n} \sum X_{i,k} X_{i,k}^T - \tilde{x}_k \tilde{x}_k^T + R_k \quad (11)$$

$$K_k = Q_{xy,k} Q_{yy,k}^{-1} \quad (12)$$

Finally, the filtering method updates the better covariance matrix and this cubature filters are used to estimate the errors. Then data are transferred into RecGNN for classification.

### C. Classification using Recurrent Graph Neural Network (RecGNN)

In this section, RecGNN is discussed. RecGNN is used to classify the seating arrangement such as reserved seating, bowl seating and stadium seating. The majority of the early GNNs were recurrent graph neural networks (RecGNN) [29]. They use the same set of parameters repeatedly to generate high-level node representations from nodes in a network. The concealed state of a node is frequently updated.

$$h_v^{(t)} = \sum_{u \in N(v)} f(Y_v, Y_{(v,u)}^e, Y_u, h_u^{(t-1)}) \quad (13)$$

Here  $f(\cdot)$  is denoted as a parametrical utility. and  $h_v^{(0)}$  is modified arbitrarily. GNN may be applied to all nodes thanks to the sum operation, even in cases where there is no neighborhood ordering or variation in the number of neighbors. The repeating function,  $f(\cdot)$ , must be a contraction mapping a function that projects two points into a latent space in order to achieve convergence. Given the neural network nature of  $f(\cdot)$ , the parameters' Jacobian matrix must have a penalty term applied to it.

RecGNN employs a GRU as a recurrent function, which reduces the quantity of steps. The benefit is that parametric constraints are no longer required to guarantee convergence. A node's past hidden state and its environment both have an impact on its current hidden state, which are described as

$$h_v^{(t)} = GRU(h_v^{(t-1)}, \sum_{u \in N(v)} A h_u^{(t-1)}) \quad (14)$$

Here,  $h_v^{(0)} = y_v$ .

In embedding, the Random Steady-state learning technique is utilized, this scales better for huge graphs. SSE performs asynchronous and stochastic changes to nodes' hidden states on a regular basis. To provide stability, the weighted ordinary of the preceding and new states is used to construct the recurrent function of SSE. This definition takes the form

$$h_v^{(t)} = (1 - \alpha) h_v^{(t-1)} + \alpha A_1 \sigma(A_2 [y_v, \sum_{u \in N(v)} [h_u^{(t-1)}, y_u]]) \quad (15)$$

Here  $\alpha$  is indicated as a hyper parameter,  $h_v^{(0)}$  is modified arbitrarily. SSE, while theoretically crucial, does not mathematically explain why repeatedly applying equation (15) enables node states to converge to fixed locations.

RecGNN classifies the seat arrangement in sports venues into reserved seating, bowl seating and stadium seating. The optimization algorithm must optimize the weight parameter of RecGNN.

**D. Optimization Using Lotus Effect Optimization Algorithm (LEA)**

The LEA is a novel evolutionary algorithm that combines efficient dragonfly algorithms for exploration, such as dragonfly movement during flower pollination, for extraction and local search operations, use the lotus effect, water on flower leaves has a self-cleaning feature [30].

**Step 1:** Initialization

Set the input parameter  $W$  's initial value, which is the weight parameter of RecGNN.

**Step 2:** Random Generation

A matrix generates an input parameter at arbitrary.

$$e = \begin{bmatrix} Y_{11} & Y_{12} & Y_{13} \\ Y_{21} & Y_{22} & Y_{23} \\ Y_{31} & Y_{32} & Y_{33} \end{bmatrix} \tag{16}$$

Here,  $e$  denoted as the arbitrary group,  $Y$  indicated as the factors of the method.

**Step 3:** Calculation of Fitness Value

Fitness function assessment uses weight parameter optimization effects and is computed using equation (17). The outcome is derived from initialized assessments and the random response.

$$fitness\ function = Optimizing [W] \tag{17}$$

Where,  $W$  denotes the better node representation.

**Step 4:** Exploration Phase

In the LEA, dragonflies carry out global pollination (biological), which is the same as the suggested algorithm's exploration stage. The method used to replicate dragonfly behavior is called the dragonfly algorithm by taking into account two ideas of food and enemy in addition to three fundamental characteristics of insect swarms: separation, alignment, and cohesiveness. Separation is the act of keeping someone from running into their neighbors. The process via which individuals match their own speed to that of others in their immediate surroundings is known as alignment. Cohesion indicates people's tendency to congregate in the middle of the neighborhood's population. Each swarm's principal purpose is survival. As a result, everyone must be enticed to food sources while staying away from opponents. Five factors, all of which might be quantitatively modeled are involved in updating the placements of the individuals in the swarm in light of these two behaviors.

The separation formula is as follows.

$$A_i^t = -\sum_{j=1}^N Y_i^t - Y_j^t \tag{18}$$

Here  $N$  is indicated as the number of individuals,  $Y_i$  the current person's place ( $i$ ) in the evolutionary iteration  $t$ , and  $Y_j$  denotes  $j$ th individual's place in the neighborhood during the cycle.

To calculate alignment, use this formula:

$$B_i^t = \frac{\sum_{j=1}^N Y_j^t}{N} \tag{19}$$

Where, at iteration  $t$  of evolution,  $Y_j$  represents the speed of the  $j$ th individual in the neighborhood.

The formula for calculating cohesiveness is as:

$$C_i^t = \frac{\sum_{j=1}^N Y_i^t - Y_j^t}{N} - Y_j^t \tag{20}$$

The following formula determines the attraction toward food sources:

$$D_j^t = Y_+^t - Y_i^t \tag{21}$$

Here  $Y_+^t$  is denoted as the position of the food supply that emerged from this phase of evolution, i.e.,  $t$  is the best-found solution.

The calculation of enemy distraction looks like this:

$$F_i^t = Y_-^t + Y_i^t \tag{22}$$

Here,  $Y_-^t$  is indicated as the adversary's position as a result of the current evolutionary cycle, i.e.,  $t$  is the worst-found response.

The dragonfly algorithm was built on the PSO algorithm's design, and its step length is similar to the PSO algorithm's velocity vector. The step or velocity vector, which is defined as follows, indicates the direction in which the dragonflies are moving.

$$\Delta Y_i^{t+1} = (aA_i^t + bB_i^t + cC_i^t + dD_i^t + fF_i^t) + w\Delta Y_i^t \tag{23}$$

Here  $a$  is indicated as the coefficient of separation,  $A_i^t$  is represent as the  $i$ th individual's separation degree in evolution iteration  $i$ ,  $b$  is indicated as the coefficient of alignment,  $B_i^t$  is represent as the  $i$ th individual's alignment,  $c$  is indicated as the coefficient of cohesion,  $C_i^t$  is represent as the  $i$ th individual's cohesion,  $d$  is indicated as the factor of the food,  $D_i^t$  is represent as the  $i$ th individual's food source  $f$  is the factor of the enemy,  $F_i^t$  is represent as the  $i$ th individual's enemy,  $w$  is indicated as the weight of inertia, and finally,  $t$  is indicated as the algorithm's iteration counter

The step vector is calculated first, followed by the position vectors, as:

$$Y_i^{t+1} = Y_i^t + w\Delta Y_i^{t+1} \tag{24}$$

When there is no solution in their area, the artificial dragonflies must fly throughout the search space with a random stride length to improve their unpredictable/stochastic behaviors. In this instance, the following relation is used to update the dragonfly positions:

$$Y_i^{t+1} = Y_i^t + Levy(g) \times Y_i^t \tag{25}$$

Here,  $g$  denotes the position vector's dimensions and  $t$  is the counter of the current iteration. To calculate  $Levy$ , the relation is given below:

$$Levy(y) = 0.01 \times \frac{r_1 \times \sigma}{|r_2|^{\frac{1}{\beta}}} \tag{26}$$

The variables  $r_1$  and  $r_2$  represent 2 arbitrary quantities between 0 and 1, whereas  $\beta$  represents a constant value. The following relation is used to determine  $\sigma$  :

$$\sigma = \left( \frac{L(1 + \beta \times \sin(\pi\beta))}{L\left(\frac{1 + \beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{\frac{1}{\beta}} \tag{27}$$

$$L(y) = (y-1)! \tag{28}$$

**Step 5: Exploitation Phase**

In the proposed algorithm, the extraction phase is local pollination, or self-fertilization. In this pollination approach, a coefficient determines the size of each bloom's growth zone in relation to the best-found blooming. Other solutions flow towards the best-found answer, which serves as the foundation for movement. The movement algorithm starts with longer steps and ends with shorter ones.

$$Y_{i,t+1} = Y_i^t + R(Y_i^t - h^*) \tag{29}$$

Here  $Y_{i,t+1}$  is denoted as the pollen position in the  $t+1$  iteration and  $h^*$  is represent as So far, this is the best pollen finding location.  $R$  is indicated as the growth region, which contracts as the algorithm iterates. In actuality, the movement steps get shorter as the algorithm progresses towards its conclusion and eventually converges to the optimal value.

$$R = 2e^{-\left(\frac{\Delta t}{M}\right)^2} \tag{30}$$

Here,  $t$  is indicated as present evolutionary iteration,  $M$  is denoted as the final iteration amount.

**Step 6:** Update the Best Solution

The process is finished if the best result is achieved.

**Step 7:** Termination

If a solution is found to be the best, the technique will terminate; otherwise, It will go through the ensuing levels until a solution is found, then go back to the step 3 fitness calculation.

## IV. RESULT AND DISCUSSION

The experiment's outcome of Optimization of Seating Arrangement in Sports Competition Venues using RecGNN-LEA method is discussed in this session. Using a Python working platform, the proposed approach is simulated under various performance criteria. Outcome of SASCV-RecGNN-LEA is analyzed with existing methods such as SASCV-CNN, SASCV-LaRSA, and SASCV-TDNN.

*A. Performance Measures*

In order to choose the optimal classifier, this is an important task. Performance parameters like recall, f1-Score, accuracy, precision, and calculation time are looked at in order to assess the performance. The confusion matrix will be utilized to scale the performance metrics, it has been decided. Scaling the confusion matrix requires the variables True Negative (TN), True Positive (TP), False Negative (FN), and False Positive (FP).

*1) Accuracy*

It is the proportion of accurate predictions to all predictions made for a given dataset. It is quantified using eqn (31).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (31)$$

*2) F1-Score*

The proposed SASCV-RecGNN-LEA technique's performance is examined using the F1-score measure. It is computed in equation (32).

$$F1score = \frac{TP}{TP + \frac{1}{2}[FP + FN]} \quad (32)$$

*3) Precision*

The number of correctly produced positive predictions is measured by a statistic called precision (P). This is computed via following equation (33).

$$P = \frac{TP}{TP + FP} \quad (33)$$

*4) Recall*

The percentage of accurate positive forecasts to all positive forecasts is determined by the recall (R) statistic. It is quantified using equation (34) below.

$$R = \frac{TP}{TP + FN} \quad (34)$$

*B. Performance Analysis*

Fig 2 to 6 shows the simulation outcomes of SASCV-RecGNN-LEA. Then the results are compared with existing methods like SASCV-CNN, SASCV-LaRSA, and SASCV-TDNN.



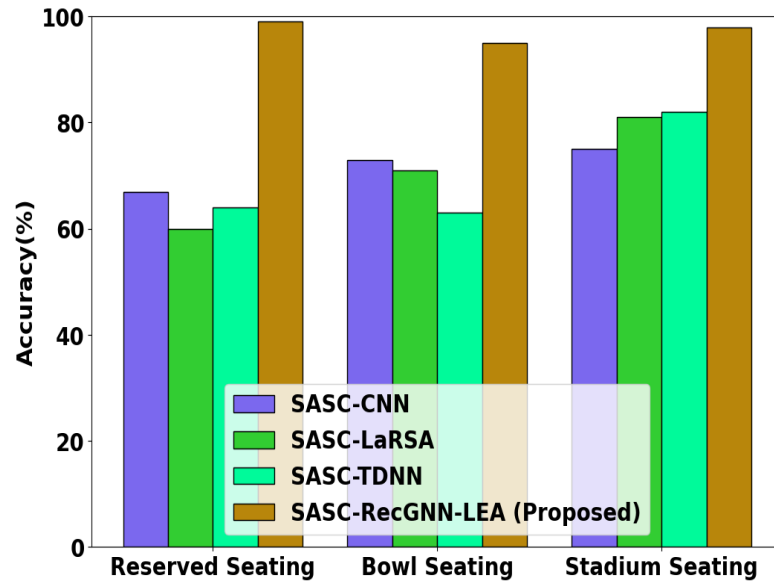


Fig 2: A comparison of the accuracy values of proposed and existing methods

A comparison of the accuracy values of proposed and existing methods is displayed in Fig 2. The performance of the proposed technique results in accuracy that are 50.51%, 20.68%, 35.87% higher for the classification of reserved seating, 20.46%, 35.62%, 23.52% higher for the classification of bowl seating, and 21.49%, 30.79%, 18.43% higher for the classification of stadium seating when evaluated to the existing SASCV-CNN, SASCV-LaRSA, and SASCV-TDNN methods correspondingly.

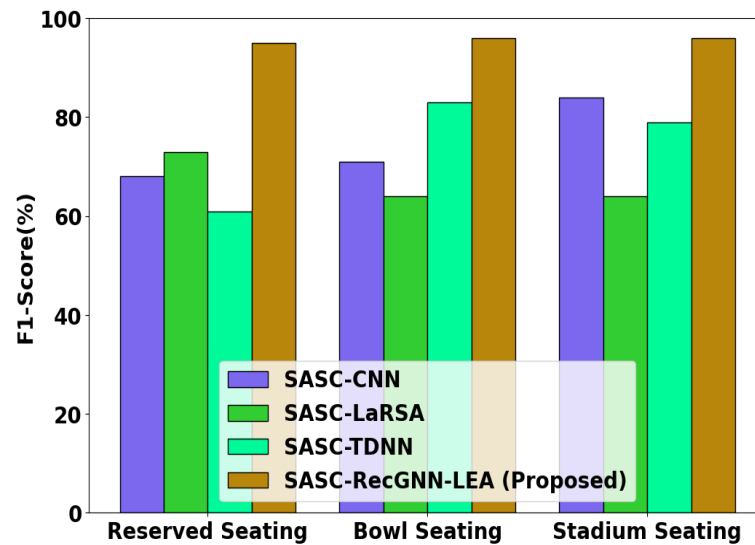


Fig 3: Comparison of F1-score values between proposed and existing approaches

Comparison of F1-score values between proposed and existing approaches is displayed in Fig 3. The performance of the proposed technique results in f1-score that are 22.58%, 21.67%, 33.89%, higher for the classification of reserved seating, 21.53%, 33.64%, 23.56% higher for the classification of bowl seating, and 21.49%, 30.71%, 18.37% higher for the classification of stadium seating when evaluated to the existing SASCV-CNN, SASCV-LaRSA, and SASCV-TDNN methods correspondingly.

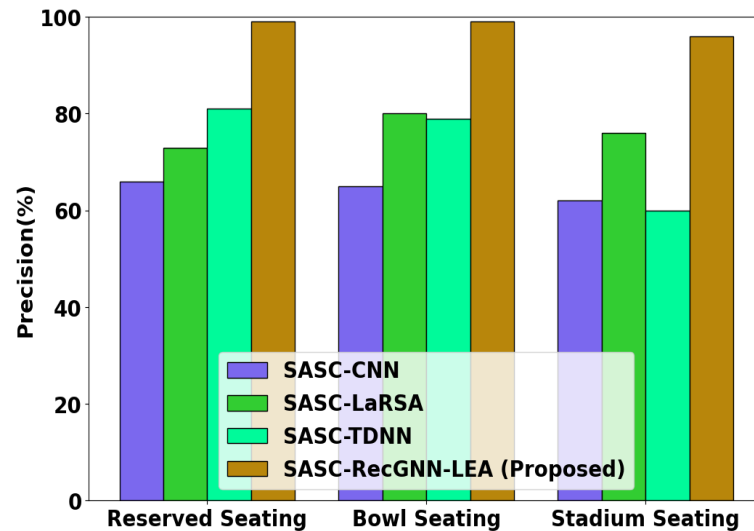


Fig 4: A comparison of precision values between proposed and existing approaches.

A comparison of precision values between proposed and existing approaches. Is displayed in Fig 4. Here, a direct comparison with existing methods is offered to show how the proposed method's precision is higher. The proposed method provides for a more extensive analysis and has higher precision than existing methods due to its wider consideration of factors. The performance of the proposed technique results in precision that are 30.62%, 21.74%, 35.81% higher for the classification of reserved seating, 21.57%, 33.59%, 23.48% higher for the classification of bowl seating, and 21.47%, 30.74%, 18.41% higher for the classification of stadium seating when evaluated to the existing SASCV-CNN, SASCV-LaRSA, and SASCV-TDNN methods correspondingly.

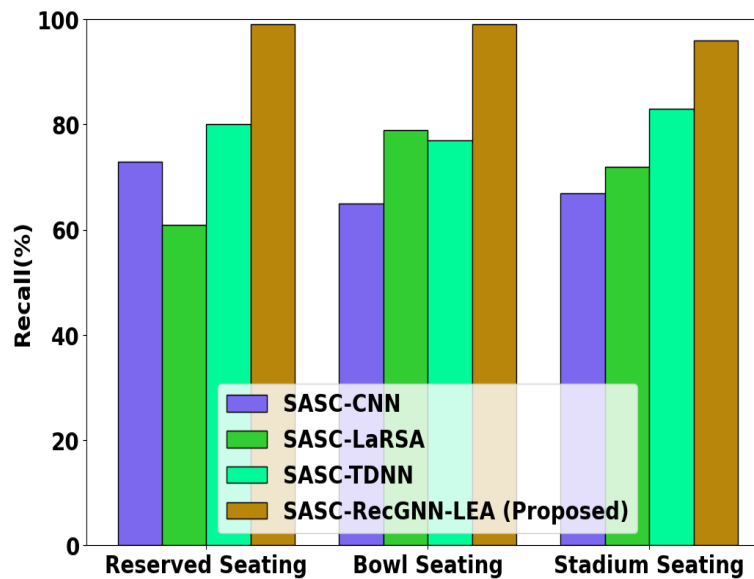


Fig 5: A comparison of recall values between the proposed and existing systems

A comparison of recall values between the proposed and existing systems is displayed in Fig 5. The performance of the proposed technique results in recall that are 23.63%, 22.77%, 31.92% higher for the classification of reserved seating, 22.38%, 31.57%, 22.50% higher for the classification of bowl seating, and 22.49%, 29.74%, 17.38% higher for the classification of stadium seating when evaluated to the existing SASCV-CNN, SASCV-LaRSA, and SASCV-TDNN methods correspondingly.

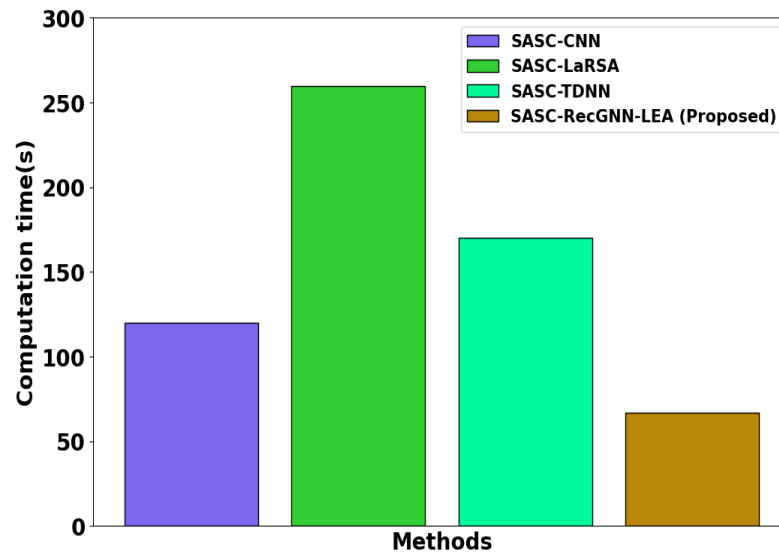


Fig 6: Analysis of computing time using the proposed and existing methods.

Analysis of computing time using the proposed and existing methods. is displayed in Fig 6. The proposed SASCV-RecGNN-LEA approach requires 5.37%, 10.22%, and 10.08% less computational time than existing methods such as SASCV-CNN, SASCV-LaRSA, and SASCV-TDNN, correspondingly.

## V. CONCLUSION

In conclusion, this research harnesses the power of Recurrent Graph Neural Network (RecGNN) to significantly train the seating arrangement model for sports venues. An essential first step is data collection where the data is acquired from Los Angeles Memorial Sports Arena seating dataset which consists of seating layout data. The ARCKF is used to process the seating dataset during pre-processing. The pre-processed data is fed to the classification where the seating data is classified using Recurrent Graph Neural Network (RecGNN) into reserved seating, bowl seating and stadium seating. The proposed method is evaluated on the Python working platform and contrasted with current approaches; it is examined in various scenarios including accuracy, f1-score, precision, recall, and computation time; the accurate identification of the recommended optimum region expanding technique has increased the accuracy of the RecGNN classifier to 97%, which is employed in the last stage of the system and shows its accuracy in identifying accuracy, f1-score, precision, and recall.

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