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Neural Network and Random Forest Algorithms for Estimation of the Waiting Times Based on the DES in ED

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***Abstract* –** This study aimed to predict patient waiting times for an ED (emergency department) unit by integrating DES (discrete event simulation) model and ML (machine learning) algorithms. The health resources in the DES model were kept constant. However, the results were obtained by including the statistical distributions of the processes in the DES. Length of stay (LOS), resource efficiency rates, patient genders, walking distance, time of processes, and age were considered input factors that affect patient waiting times. Prediction data were calculated using Neural Network (NN) and Random Forest (RF) models from ML algorithms. Testing and training phases of ML algorithms are set to 20% and 80%. The RF model performed best with low RMSE, MSE, MAE, and high R^2 values. This model's RMSE, MSE, MAE, and R^2 values were calculated as 2.81, 1.67, 0.88, and 0.996, respectively. As a result, this study suggested integrating DES and ML models to overcome many factors, such as satisfaction, cost, and quality, with the intense human factor in service sectors with dynamic structures.

Keywords – Machine Learning, Discrete-Event Simulation, Neural Network, Random Forest, Waiting Time

I. Introduction

Researchers use different methods in studies that require a long time and cost [1]. The beginning of these methods is generally engineering applications [2]. It is challenging to monitor factors such as time, satisfaction, cost, and quality, especially in the human factors processes in the service sector [3]–[5]. For this reason, engineering applications are inevitable in sectors with such factors. In this study, DES and ML methods were used to estimate patient waiting times, which is one of the critical problems of the health sector [1], [6]–[9].

DES is an engineering application created in a computer environment to track the resources in mobile systems [10], [11]. This application is widely used in many fields, such as health, production, transportation, logistics, education, and economy [8], [12], [13]. In this study, patient waiting times were calculated in the ED unit using the DES model. The DES model has been used in many studies in the field of health and has contributed to solving many problems, such as patient satisfaction, waiting time, and cost [14], [15].

In one study, using DES significantly increased the number of patients treated in the ED unit and reduced patient waiting times [16]. In another study, the DES model tried to reduce the cost of a patient to the hospital and ensured the optimal level of patient resources [17]. Ahmad and Alkhamis created the DES model to confirm the employment of healthcare workers at an optimum level, significantly reducing cost and waiting time [18]. In another study, the duration of a patient's stay in the ED unit was minimized by using the DES model [19].

In this study, the validity of the prediction data was ensured by using ML algorithms and DES techniques [6]. Patient waiting times were estimated by applying the data obtained in the DES model to ML algorithms. ML algorithms are widely preferred in the health sector and used in many areas [7]. Especially in medical subjects, ML algorithms are widely used. In this study, NN and RF models from ML algorithms were used. In one study, RF (random forest), GB (gradient boosting), and AB (adaptive boosting) algorithms were used to estimate the number of patients treated and patient waiting time in terms of cost [6].

There are four sections in this study. In the first part, there is a literature review of the methods used in the study. Information about the methods used in the study is given in the second part of the research. The numerical results of the study are discussed in the third part. Finally, the positive contribution of the proposed proposition in the study to the literature has been expressed.

II. MATERIALS AND METHOD

In this study, the results obtained for an ED created in the DES model were run in ML algorithms to get the estimation data of the patient waiting times. The methodology part of this study consists of three main parts: DES, ML, and performance measurements of ML algorithms.

2.1.Discrete Event Simulation for ED Model

In this study, a DES model was created that includes the characteristics, physical structure, and resources of an ED in a Hospital. The DES model was created in 3D using the Flexsim HC computer program. The DES model developed for this study is visualized in Figure 1.

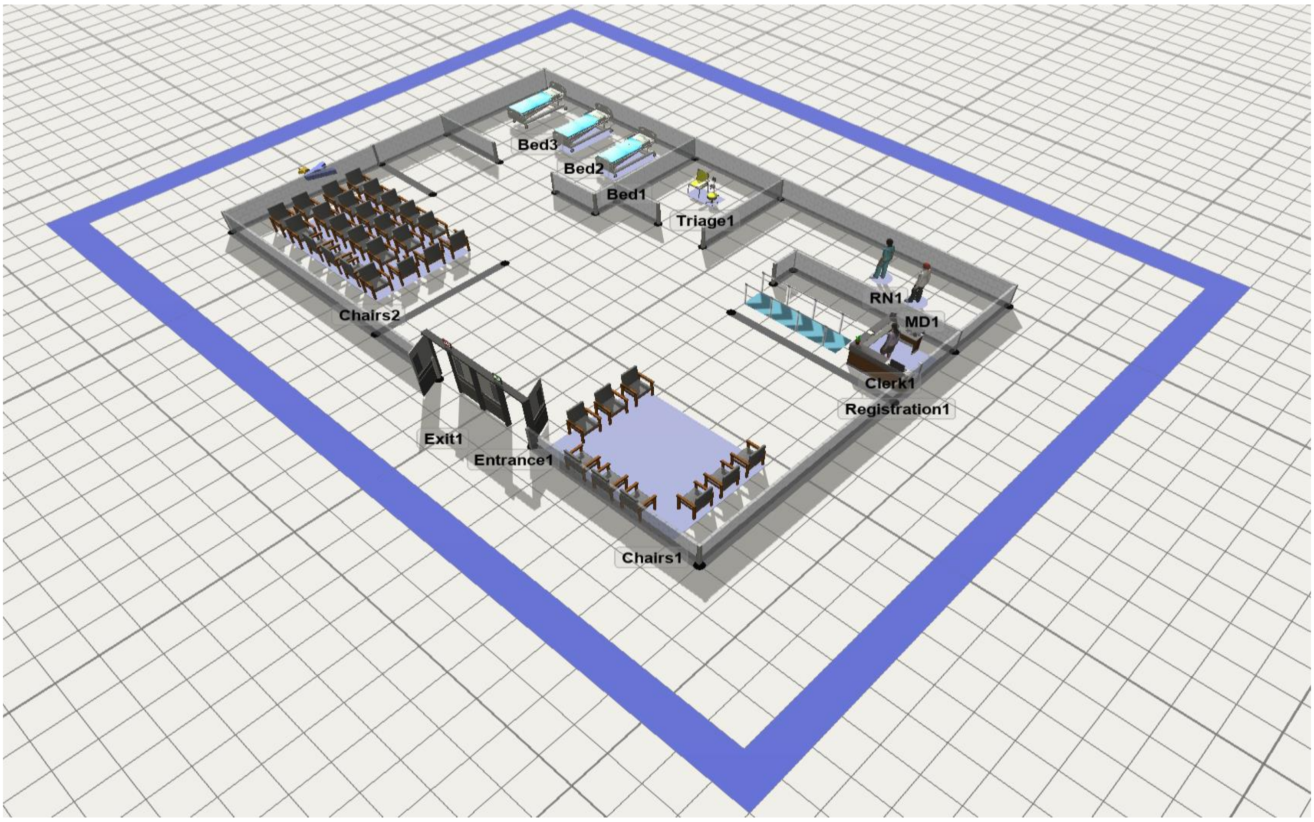

Figure 1. The DES model of an ED

By running the DES model for 24 hours, one-day data was obtained. Generally, the data are derived by creating one for each ED source number (excluding the number of beds). The characteristics of the sources in this model are shared in Table 1. Based on the DES model, the flow chart that a patient should follow between the time of entry and exit from the hospital is shown in Figure 2.

Table 1. The features of the resources in ED

Types	Notations	Numbers
Medical Doctors	MD	1
General Nurses	Nurses	1
Check-in Clerks	Clerks	1
Triage Chairs	Triage	1
Exam Beds	Beds	2

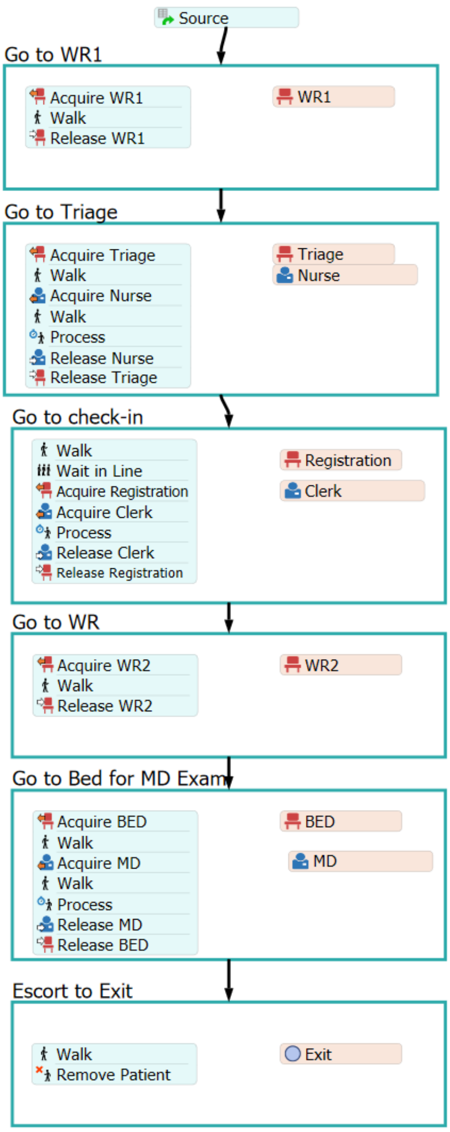

Figure 2. The flow chart of patients for the process of ED

Depending on the patient flow chart, a patient needs time in three main processes. A patient encounters the triage process, the check-in process, and finally, the doctor's examination/treatment process. Apart from these processes, if the sources in the ED are concentrated (if they are in process), the patients have to wait in the designated areas. Statistical data of these processes are shared in Table 2.

Table 2. The distribution of process and arrival rate

Parameters	Distribution
Arrival Rate	exponential(0, 15, get stream(activity))
Triage Process	exponential(0, minutes(4), get stream(activity))
Check-in Process	exponential(0, minutes(2), get stream(activity))
Exam Process by MD	exponential(0, minutes(10), get stream(activity))

2.2.Machine Learning Algorithms

In this study, the data obtained from DES was used in ML algorithms to obtain predictive data. Length of stay (LOS), resource efficiency rates, patient genders, walking distance, time of processes, and age were considered input factors that affect patient waiting times. Thus, integrating DES and ML algorithms will significantly contribute to the estimation method. In this study, Neural Network (NN) and Random Forest (RF) algorithms were preferred for prediction data. These algorithms were created in the Orange 3.34 computer program with phyton software, and the prediction data were calculated. The model developed for ML algorithms is shown in Figure 3.

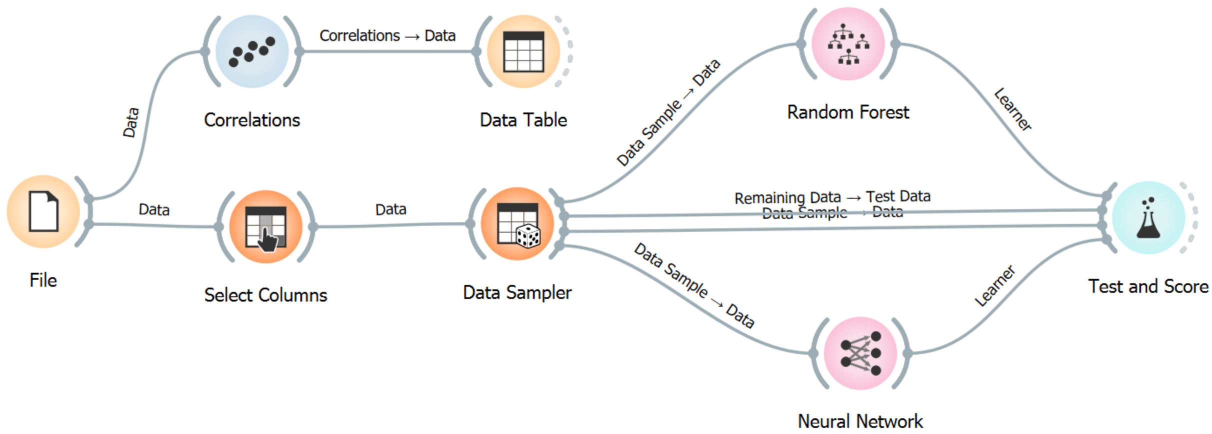

Figure 3. The model of ML algorithms

2.3.The performance of ML algorithms

The four different performance measurement criteria were used to verify the validity of the results of the prediction data obtained from the ML algorithms. While three of these criteria represent the margin of error, one represents the accuracy coefficient. RMSE (Root Mean Square Error), MSE (Mean Squared Error), and MAE (Mean Average Error) values represent the margins of error of ML algorithms [20]. Margins of error should be low in ML algorithms. However, the higher the coefficient of determination (R^2), which is the accuracy coefficient, the more accurate the validity of the estimated values obtained in the ML algorithms [21].

III. Results

The numerical results of this study are examined under the DES model and ML algorithms sections.

3.1.The results of DES model

The DES model was run primarily by considering the available resources. Since no changes were made from the sources, only the DES model was run as a single scenario. However, since the processes and patient arrival times in the DES model are statistically distributed, the scenario was run in five replicates. The number of patients treated according to the current DES model is given in Table 3.

Table 3. Number of patients treated per day based on the DES model

ScenarioID	RepNum	Throughput
1	1	73
1	2	89
1	3	96
1	4	91
1	5	86

Due to the limited number of resources used in the DES model, the working rates of some resources are very high. Intensively working resources cause patients to wait. Two types of resources, location and human-based, cause patients to wait. For this reason, some patients cannot receive health care as soon as they reach the ED unit. Such negative situations cause patients to wait for a long time. The average waiting times of the patients as a result of running the DES model with the current situation five times are given in Table 4.

Table 4. Average patient waiting time based on the DES model

ScenarioID	RepNum	WaitForLocation	WaitForStaff
1	1	8.840056	5.977856
1	2	7.137227	5.706092
1	3	23.16126	8.382226
1	4	13.8348	6.97756
1	5	21.33921	6.336999

The sum of the time required for the processes and the waiting times for a patient to apply to an ED unit is defined as the length of stay (LOS). That is, the time from the time of arrival of a patient to the ED unit until the same patient leaves the ED unit is expressed as LOS. The mean LOS values of the DES model in this study are given in Table 5.

Table 5. Average LOS time based on the DES model

ScenarioID	RepNum	Staytime
1	1	32.29799
1	2	30.65016
1	3	50.61048
1	4	40.80772
1	5	46.56522

The working rates of the resources in the ED unit affect the wait and LOS values of the patients. The efficiency ratios of the resources were calculated by running the DES model for only one day. For this study, the efficiency rates of the resources by running the current model are given in Table 6.

Table 6. Efficiency rates of resources depending on the DES model

ScenarioID	RepNum	Subset	Time	Utilization
1	1	MDGROUP	Day 1	53.44%
1	1	NURSEGROUP	Day 1	18.87%
1	1	CLERKGROUP	Day 1	9.08%
1	2	MDGROUP	Day 1	58.52%
1	2	NURSEGROUP	Day 1	30.22%
1	2	CLERKGROUP	Day 1	11.82%
1	3	MDGROUP	Day 1	74.72%
1	3	NURSEGROUP	Day 1	27.21%
1	3	CLERKGROUP	Day 1	12.71%
1	4	MDGROUP	Day 1	73.58%
1	4	NURSEGROUP	Day 1	27.18%
1	4	CLERKGROUP	Day 1	11.42%
1	5	MDGROUP	Day 1	60.69%
1	5	NURSEGROUP	Day 1	25.09%
1	5	CLERKGROUP	Day 1	13.13%

The waiting times of the patients were calculated by running the DES model for five replicates. These times are shown in Figure 4. Estimation data were obtained using historical patient waiting time data in NN home RF models. Estimated data of ML algorithms are shared later in this section.

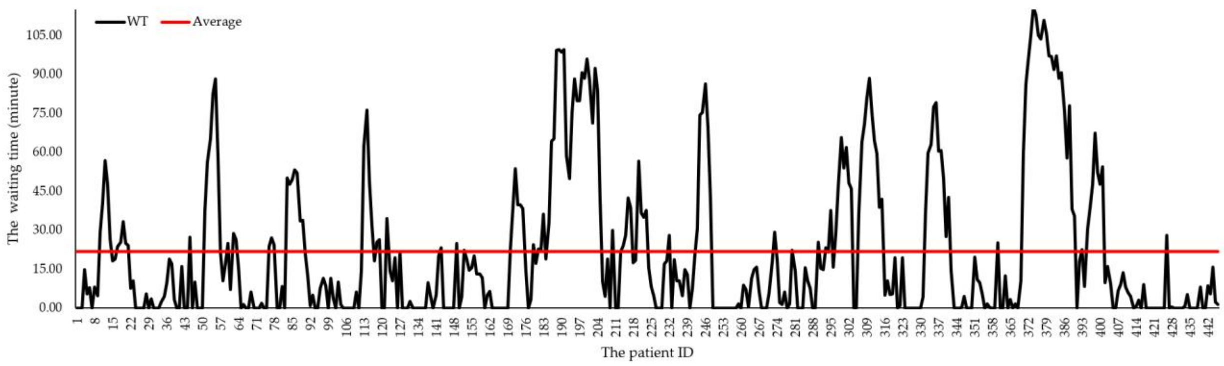

Figure 4. The time patients wait to receive service in the ED unit

3.2.The results of ML

In this study, NN and RF algorithms were run to obtain the prediction data. The data on patient waiting times obtained from DES have been estimated using these algorithms. The measurement values of the performance criteria were calculated to verify the validity of the prediction data obtained from these algorithms. Training and testing phases of ML algorithms are set to 80% and 20%. These values are shared in Table 7.

Table 7. Performance measurement values of algorithms

Algorithms	Stage	Rate	MSE	RMSE	MAE	R^2
Random Forest	Test Stage	80 %	12.456	3.529	2.001	0.987
Neural Network			90.485	9.512	6.124	0.903
Random Forest	Train Stage	20 %	2.813	1.677	0.876	0.996
Neural Network			49.138	7.010	4.845	0.937

The RF algorithm provided the best performance in both the training and testing phases of the ML model. The MSE, RMSE, MAE, and R^2 values in the training phase of this model were calculated as 2.81, 1.67, 0.88, and 0.996, respectively. The MSE, RMSE, MAE, and R^2 values in the testing phase of the same algorithm were calculated as 12.46, 3.53, 2.01, and 0.987, respectively.

The NN algorithm performed poorly in both the training and testing phases of the ML model. The MSE, RMSE, MAE, and R^2 values in the training phase of this model were calculated as 49.138, 7.01, 4.85, and 0.937, respectively. The RMSE, MSE, MAE, and R^2 values in the testing phase of the same algorithm were calculated as 90.485, 9.512, 6.124, and 0.903, respectively.

The comparison of the waiting times of the patients with the actual patient waiting time depending on the RF and NN algorithms is given in **Figure 5**.

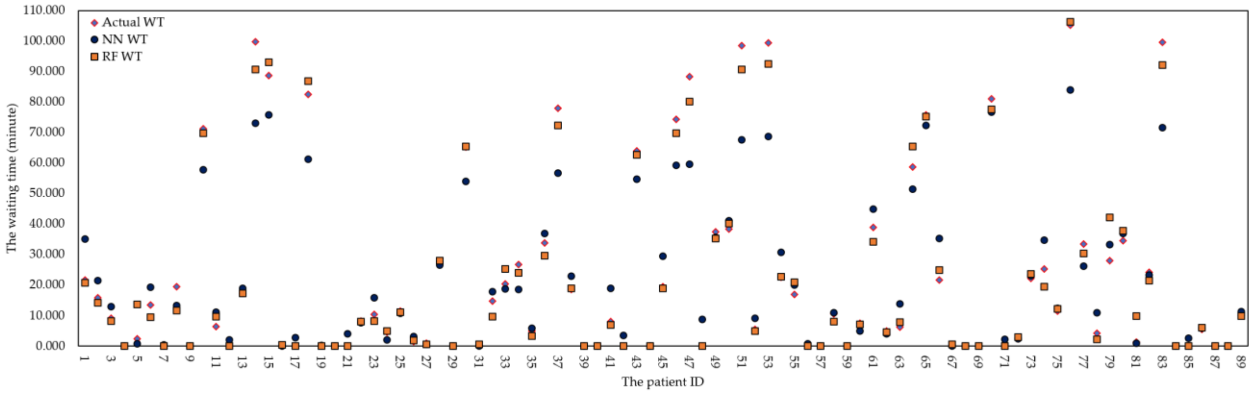

Figure 5. Patient waiting times depending on RF and NN algorithms

IV. CONCLUSION

This study integrates ML algorithms and DES techniques, significantly contributing to long-term and high-cost studies. In this study, patient waiting times were calculated by creating a DES model of a hospital's emergency department. Patient waiting times obtained from the DES model were applied to RF and NN models from ML algorithms to obtain predictive data. Among these algorithms, the RF model, which has a low error and high accuracy, showed the best performance. The NN model, on the other hand, provides a lower level of performance than the RF model, and the prediction data is calculated. This study emphasized the ease of obtaining concrete and valid results with DES and ML models, which are engineering applications in health management.

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