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Optimal Equipment Capacity Planning in the Neonatal Intensive Care Unit with Simulation-Optimization Approach

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Highlights

- The capacity planning for the neonatal intensive care unit of a hospital is addressed.
- The simulation-optimization approach is proposed for the problem with three objectives.
- Incubators, ventilators, and nitric oxide devices are considered with different levels of patients.
- Each model results are evaluated by curve fit method to find the best quantities of equipment's.

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Abstract

Capacity planning should be performed to balance investment costs and benefits of investing to meet the current and future demand in intensive care units. Having a high capacity to increase patient admission will lead to unutilized capacity in some periods, thereby increasing costs. On the other hand, patient admission requests from inborn and transported patients might be rejected due to lack of equipment. It should be considered in terms of cost-effectiveness and patient health; therefore, optimal equipment capacity must be determined. In this study, the optimal capacity planning problem has been considered for the neonatal intensive care unit of a hospital adopting the simulation-optimization approach. A discrete event simulation model is proposed for a neonatal intensive care unit in Adana, Turkey. Then, the optimization model identified the optimal numbers of incubators, ventilators, and nitric oxide devices to maximize equipment efficiency and minimize total inborn patient rejection and transport ratios. Three different resource allocations are presented, and the best is obtained from these three objectives as 72 incubators, 35 ventilators, and three nitric oxide devices. The application results obtained have revealed that the rejection and transport rate, which is found to be 1.12% in the current situation, can be reduced to 0.2% with different numbers of equipment and that equipment efficiency can be achieved with optimal quantities of each equipment. The results of the study can help the decision-makers when minimum transport and rejection ratios are critical which almost all intensive care units are required. Furthermore, the proposed simulation-optimization model can be adapted to different neonatal intensive care units having the same characteristics.

1. INTRODUCTION

Intensive care units (ICUs) are vital in healthcare. The capacity planning of these units has been observed as significant, particularly during a pandemic, when intensive care beds and ventilators are required by many people. Some patients need ventilatory support, as the pandemic, which has caused many deaths worldwide, affects the respiratory tract; ICU and ventilator capacities have been exceeded in some countries, and serious difficulties were experienced to the extent that hospitals even had to select patients to be admitted [1]. ICUs come in three levels: level 3, level 2, and level 1, depending on the characteristics of the care they provide and the characteristics of the patients admitted [2]. ICUs are divided into three groups: intensive care units for adults, pediatric intensive care units (PICU), and neonatal intensive care units (NICU). The total number of beds in intensive care units (ICUs, PICUs, and NICUs) in hospitals included in the health system in Turkey is 38098, 12402 of which belong to NICUs [3]. ICUs are divided into levels because general child health and children's diseases require different intervention and treatment procedures based on age group, so age groups bearing the same characteristics must be categorized under

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the same group. Hereunder, the neonatal period covers the 28 days starting from the birth of the neonate, and these neonates might need to be admitted to the NICU within this 28-day period.

Neonatal born in one center and transferred to another center or who have more advanced needs might be negatively affected by the transport process. Especially for patients who require advanced care, such as low birth weight neonatal, the risk increases. In many studies, it has been reported that morbidity (the condition of suffering from a disease or medical condition) and mortality (the state of being subject to death) are reported to be better for neonatal born in perinatal centers that can provide tertiary care. Neonatal such as preterm and very low birth weight transplanted who are born in primary and secondary healthcare institutions and transferred to tertiary ICUs have worse mortality and morbidity rates [4-6]. In the study conducted by Helenius et al. [7], evidence suggesting that birth in centers not holding level 3 service competence was associated with adverse outcomes compared with birth in a center providing level 3 service competence was presented. Accordingly, it can be said that the transport of some neonates is not preferred, as it might lead to adverse outcomes in terms of the neonate's health.

The provision of not only beds but also the equipment necessary for advanced intensive care services provided to patients with aggravated health status is important in the ICUs of hospitals. The most significant of this equipment are ventilators and nitric oxide devices, which are used in patients that require further treatment and are vital in some patients receiving ventilator treatment. This able spacer is connected to the ventilator during treatment.

Nitric oxide treatment is a difficult and expensive procedure that can be employed in advanced centers and is life-saving when the treatment of the patient is retrogressing. Nitric oxide devices are available in few ICUs, as they are costly and can be applied in advanced healthcare centers only. Studies reveal that the average duration of therapy is between 48 hours and 96 hours, and many randomized studies indicate that 90% of the neonates treated with nitric oxide therapy are released from the therapy within one week [8].

As patients in ICUs are in a critical period, their requests for admission to a hospital should not be delayed but rather accepted immediately. Delays in the initiation of therapy and undertreatment resulting from delayed admission are known to affect the patient negatively. Rejection of patients' requests for admission to a hospital and referral thereof to centers providing the next level of healthcare due to inadequate equipment might lead to adverse outcomes in terms of patient health [9]. For this reason, long- and short-term capacity planning must be performed to minimize the rejection of requests for admission to a hospital and maximize patient admission. In the meantime, optimal capacity planning is an issue that must be addressed carefully, as the cost of ICU equipment is quite high. This is necessary to provide sustainable health services that meet a certain quality standard.

Inter-hospital intensive care patient transport might be performed for many reasons, such as inadequacy of equipment or the absence of an empty incubator in the hospital where an infant was born. Transport of the patient to a more advanced hospital might be required, as a hospital might not have the capacity to provide patients in different levels of ICUs with the required healthcare services [10].

In addition to including many risks for patients, neonatal transport is an expensive service requiring a special team and special equipment. The development of serious complications in neonates due to neonatal transport has been reported [11]. Minimization of the transport of patients born in the center is desired out of concern for patients and for many other reasons, such as cost.

The simulation-optimization model is developed to meet the demand for hospitalization in terms of the health of the neonatal in need of intensive care, reduce the transport of the neonatal born in the hospital to another hospital, and determine the optimal quantities of each equipment that the neonatal under treatment may need. In this scope, it is aimed to determine the optimal quantities of each equipment using data obtained from a health institution. First, a simulation model was proposed for the existing system, and a multi-purpose approach was followed to provide minimum transport and maximum equipment efficiency by adding the optimization approach under the current constraints.

2. LITERATURE REVIEW

The simulation-optimization modeling method is commonly used today for different purposes in health systems. Decision-making problems in healthcare are generally complex and have a problem-specific nature. Therefore, decision-making problems are typically handled by adopting the simulation approach. Simulation practices in the health industry have been in use for many years, the first examples of which date back to the 1960s [12]. The simulation-optimization modeling method is used to determine the optimal bed capacity in hospitals. Simulation modeling studies on optimal bed capacities have been conducted for operating rooms, emergency services, and ICUs in hospitals.

Bowers used simulation modeling to analyze the relationship between resource utilization and daily demand, in addition to the balance between such demand and the number of beds in operating rooms in centers providing heart and lung surgery services [13]. In the study conducted by Haghighinejad, scenario analyses aimed to determine the number of patients waiting and reduce the length of queues and waiting periods; such analyses were performed using simulation modeling [14]. Zychlinski developed a stochastic simulation model to evaluate the results of the mathematical fluid model, to ensure the optimal number of beds, minimum cost, and significant reductions in the number of patients waiting in the geriatric care service, and then compared the results [15].

Intensive care services differ from other services in a hospital and from one another in terms of patient characteristics and administration. The problem of optimizing the bed capacity of intensive care services is a widely worked topic in recent years [16-20]. Studies aiming to determine the bed capacity in ICUs, on the other hand, are analyzed by making many classifications according to the type of ICU, uncertainties in problem variables, the modeling, and the solution approach [21, 22]. Simulation modeling studies conducted in three different types of ICUs, namely ICU, PICU, and NICU, are available. Simulation studies in ICUs were conducted by different studies such as [23-28]. In the NICUs, on the other hand, Kokangül conducted simulation modeling studies [29].

In determining the optimal number of beds, random variables such as patient admission policies, the time between patients' arrivals, and uncertainties of their variables require different modeling and solution approaches. Literature studies were classified and evaluated considering these variables and applications. In the simulation models of ICUs, a statistical approach suitable for stochastic uncertainties in the problem variables must be determined. In the studies performed, the period between patient arrivals at the hospital and the lengths of hospital stay (LOS) are typically handled stochastically. The LOS was averaged in few studies conducted recently [30]. As seen in the studies in the literature, patient arrivals were taken as stochastic or average. In this study, since the model better reflects the real system, patient arrivals and hospitalization periods were taken as stochastic.

Linear and nonlinear optimization simulation models have been developed for bed capacity planning in ICUs. Nonlinear modeling was observed to be more common and be used by the studies [23-25,29,31,32].

Simulation models can be modeled stochastically or deterministically. Queueing models and discrete event simulation models were used in bed capacity management and planning with stochastic modeling. Queueing model simulation was used [23-25, 31]. Rodrigues et al. [33] and Akçali et al. [30], on the other hand, determined bed capacity with network flow modeling. In our study, due to the patient admission policy, the patient is rejected if there is no incubator available. Since the patient could not be kept waiting, the queuing model was not applied in this study.

In the literature research reviewed thus far, bed capacity studies performed in NICUs were evaluated only in terms of incubator optimization. However, since the admission of some patients depends on specific devices together with the incubator, it is necessary to consider the special devices used in the treatment of the patients in the simulation-optimization studies. In recent studies, this approach has begun to be adopted. Due to the concentration and inadequacies experienced in ICUs due to the recent pandemic, studies relating to bed capacity planning are observed to have increased. Weissman et al. [26] proposed a basic model to predict the timing of fluctuations in the clinical demand for ICU beds and the number of ventilators in three hospitals in Philadelphia for COVID-19 patients using Monte Carlo simulation according to the best- and worst-case scenarios. Shoukat [27] developed a simulation model related to the demand created by the increasing number of COVID-19 cases in Canada for admission to a hospital and intensive care and the extent to which isolation could delay the peak of the pandemic, performing scenario analysis related to time when current capacity might be exceeded upon arrival of the peak of the pandemic. The study conducted by Oakley at al. [28] proposes a new bed capacity problem method with the stochastic symbiotic simulation model. The symbiotic simulation model was considered to be short-term operational decision-making.

As observable in the literature studies presented above, many studies were conducted to determine the optimal bed capacity in neonatal and other ICUs. As bed capacity planning is commonly studied, no studies aiming at the optimization of other equipment of the ICU integration have been encountered. The main contribution of this study is that it proposes a simulation optimization to determine the ideal numbers of incubators, ventilators, and nitric oxide devices in NICUs where ventilator and nitric oxide device assistance are being provided. Another original contribution is to make an optimal capacity decision for resources according to the distribution curves produced from the outputs of the optimization models.

3. METHODOLOGY

The proposed methodology for determining the optimal resource allocations in the NICUs includes the steps as follows:

- The data of the system is collected, and distributions are fitted for input modeling of the simulation,
- The simulation model is built under the conditions with given characteristics,
- The running conditions (warm-up and number of replications) of the simulation model are determined in the output analysis section,
- Three optimization models (with different objectives under the same constraints) are applied to the simulation model, and the results are obtained from the models,
- Curve-fitting is applied for the data obtained from the optimization models and the current system's simulation model to find the best resource capacities,
- The best system is evaluated, and the results are interpreted.

3.1. Problem Description

ICUs are one of the most critical departments of hospitals. The reason for this is that although it is not possible for patients to wait in intensive care services, a service is provided in a race against time due to emergency conditions of patients. The problem in this study pertains to the management of intensive care for these reasons. All ICUs have common points and different features. During the pandemic, how critical it is for ICUs to meet the needs and consequences that may be caused by patient admissions and refusals was closely observed. However, it has been seen that the intensive care capacities are not only considered to be a bed but also other equipment critical to the sustainability of the treatment. For example, during the pandemic, the insufficient number of respiratory support devices in many countries led to major problems. Functioning independently from this process, neonatal intensive care has similar characteristics to the process in terms of its structure.

The intensive care system examined in this study was considered to be neonatal intensive care. In this type of intensive care, neonatals are hospitalized in incubators. However, ventilator and nitric oxide devices are included for some health problems. These devices are used during treatment if necessary and might be required for such treatment methods, especially in patients who have respiratory and/or circulatory failure, such as congenital heart disease and lung pathology. The patient's need for these devices is already present at the time of hospitalization, or such a need might occur depending on the course of the disease in the patient whose treatment process continues in the ward. There is no queuing policy (i.e., patient waiting if there is not enough equipment at any level).

For many reasons, it is not desirable for patients who applied to the NICU to be rejected or transported to another hospital due to lack of equipment. Therefore, it is desirable to minimize patient rejection and transport. First, as stated previously, transport is not preferred in neonatal intensive care patients due to complications that might occur due to transport. Second, the doctor does not wish to transport a patient whose treatment is ongoing due to a missing device (ventilator, nitric oxide). Third, the patient's health may be adversely affected if he or she is unable to accept transport to the advanced hospital due to a lack of equipment in other hospitals. Finally, the hospital administration does not prefer to transport a patient born within its own organization to another hospital in terms of service quality.

In this context, an approach has been introduced for the planning and optimization of incubators, ventilators, and nitric oxide devices, which are critical resources in ICUs. It is thought that this situation will reflect the actual operation more accurately. In the approach examined, first, the modeling of the entire process with uncertainty was provided with simulation modeling. Afterward, simulation-optimization modeling was performed by solving different optimization models for three different objectives. Moreover, the ideal quantities of each equipment (incubator, ventilator, and nitric oxide device) were determined by evaluating the results of the simulation-optimization model made using three different optimization models (considering different performance criteria) created via experimental design and distribution fitting. Thus, the proposed approach has been provided to be generalizable. The flow of the system in the neonatal unit is presented in Figure 1.

3.2. Data Collection and Input Modelling

The NICU where the study was conducted can admit patients at three levels (Levels 1, 2, and 3) based on the services provided. As the arrival of patients for each level will have different characteristics, attempts at the assimilation of arrivals who differ depending on the level of ICU applied to, and sources of uncertainty according to the duration of treatment, to theoretical statistical distributions were made. Arrivals were considered to be inborn and transported, since the variance in the duration of therapy depending on whether the patients were inborn or transported will be another cause of uncertainty. The duration of therapy, on the other hand, varies according to the level of the patient only.

A prospective study was designed in the data collection due to the lack of hospital data investigated, and data was collected using patient information forms. These forms included information such as patient admission and rejection details that can be used during modeling, thus ensuring validation of the approach proposed.

In the forms prepared, patients born in the maternity unit inside the hospital were considered to be inborn, while those born in different hospitals were considered to be transported. Acceptance and rejection forms were prepared for patients who requested to be admitted to the NICU. The request for admission to the ward is first forwarded to the doctor responsible for patient admission. The patient is then admitted to the service according to the patient's condition and the occupancy of the devices. Otherwise, the patient is rejected and entered the prepared rejection form. In these acceptance and rejection forms, the requests for admission to the NICU (infants born in the obstetrics center inside the hospital) were marked as two separate admissions, namely in-hospital and out-of-hospital (patients born in other centers and required hospitalization for treatment). The application date and level of each patient who applied with a request for hospitalization were marked on the forms. In the patient admission forms, the admission and discharge dates of the patients, the ex or transport status of the patient, and the dates of status were recorded in the patient admission form. Meanwhile, in the rejection forms, information such as the application date and whether the reason for rejection is related to devices is included. The data collection process covers the working days from January 1, 2019 to December 31, 2019. The dates of arrival at the hospital of these patients, admission or rejection, the dates the patients moved out of the system, and the patients' status at the time they moved out of the system were recorded. Moreover, the dates on which the patients were connected to a ventilator and nitric oxide devices and when they left the device were recorded, as well. Data from 546 patient admission and 49 patient rejection forms were recorded and prepared for use in the modeling.

Upon specification of the system and problem and in obtaining the necessary data, data analyses were performed to develop the simulation model first. Variables such as the period between patients' arrivals at the hospital and the service times were modeled as random variables with a specific statistical distribution and were included in the system. Paying attention to their levels and origin of arrival (inborn or transported), the most suitable distribution for patients' arrivals and service times were obtained using ARENA simulation software with "Input Analyser." With the Chi-squared test, the acceptability of distributions according to the "p" value was evaluated at alpha = 0.05 safety level. P-value shows the probability under the no difference condition that means the critical point for observed and expected values. Statistical distributions obtained for arrivals are presented in Table 1. The arrival of patients with high p levels (p > alpha) and log-normal distributions was identified. Theoretical statistical distributions accommodated for service period variables are displayed in Table 2. For p-values not seen in data that does not conform to any distributions, such data was assumed to conform to a triangular distribution.

Table 1. *Analysis results of arrival data*

Random inter-arrival times	Fitted distribution with parameters	p-value of fitting
Level 1 patient (inborn)	Weibull (2.77, 1.22)	0.709
Level 2 patient (inborn)	Lognormal (1.3, 1.1)	0.194
Level 3 patient (inborn)	Lognormal (3.97, 5.09)	0.339
Level 1 patient (outborn)	Lognormal (3.97, 5.09)	0.339
Level 2 patient (outborn)	Lognormal (1.79, 1.71)	0.142
Level 3 patient (outborn)	Lognormal (2.57, 2.95)	0.75

Table 2. *Analysis results of treatment data*

Random service times	Fitted distribution	Parameters	p-value of fitting
Level 1 treatment	Triangular	(1,3.5,8)	-
Level 2 treatment	Triangular	(0.5, 6, 37.5)	-
Level 3 treatment	Erlang	(9.31, 2)	0.228
Ventilator treatment	Weibull	(6.15, 0.864)	0.213
Nitric oxide treatment	Triangular	(1,4.125,15)	-

3.3. Model Building

The system modeled in the study is stochastic as it contains dynamic, random input elements that change in time. Inborn and transported patients admitted according to their levels might keep a vacant incubator and/or other equipment occupied, as well. If the incubators are full, the patient is rejected anyway. In all levels, the patient needs an incubator for hospitalization. A patient can receive treatment only in an incubator or with an incubator and a ventilator depending on the disease. Other characteristics of the recommended system are as follows:

- Each patient applies to the service independently with different diseases; therefore, requests for admission to the NICU are independent from one another.
- A queueing policy is not followed in the neonatal unit.
- 30 ventilators, one nitric oxide device, and 66 beds are available in the current system.
- One ventilator per three incubators should be provided for patients in level 3 ICUs.
- Nitric oxide devices are used together with ventilator devices.

There is no queuing policy for the patient to be held if there is not enough equipment at any level. When a lack of adequate equipment is the case, patients are transported to other hospitals. The flow of the system in the neonatal unit is presented in Figure 1. The system, whose characteristics have been specified, was modeled using ARENA simulation software; the results were obtained accordingly. The ARENA model is illustrated in Figure 2.

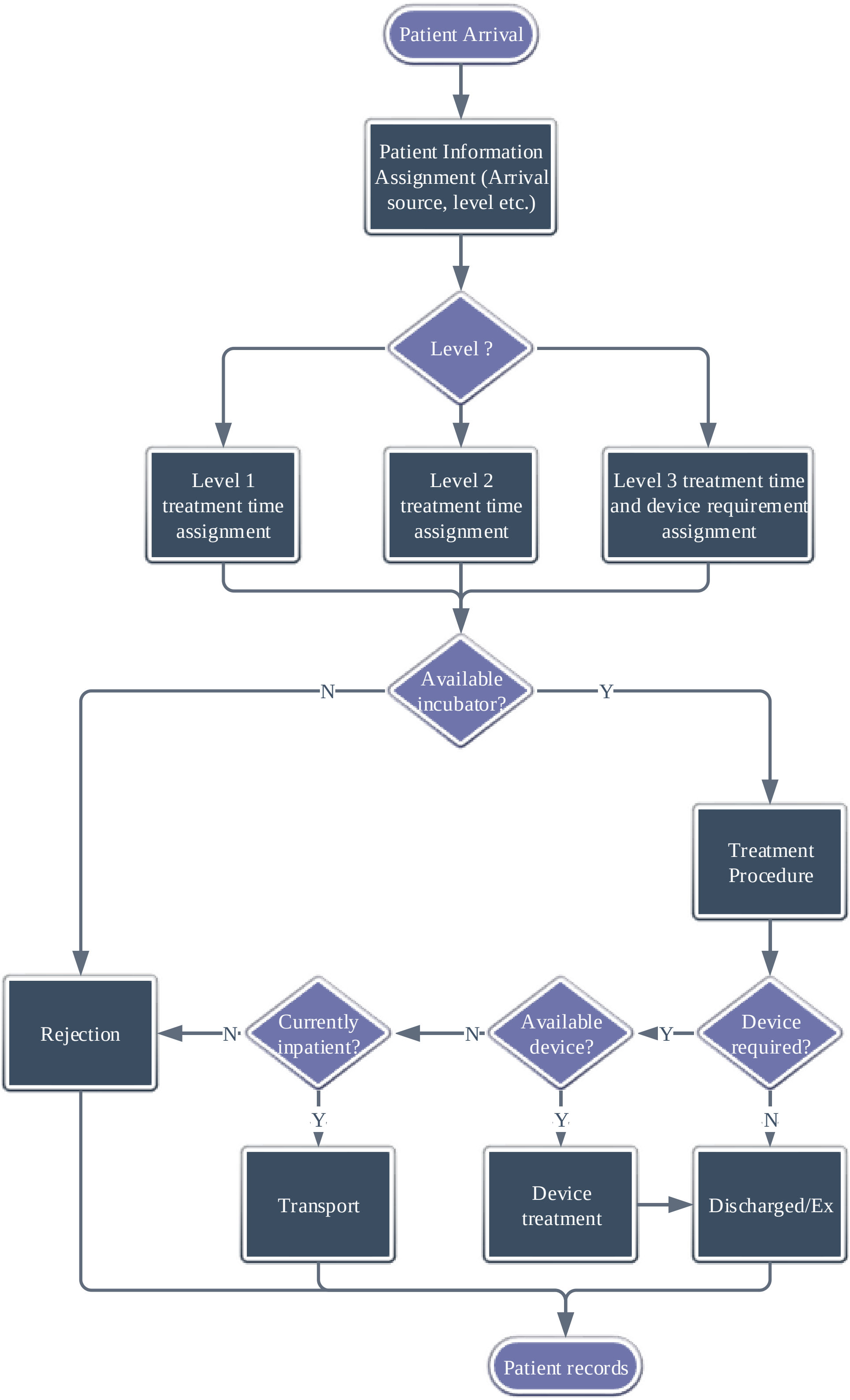

Figure 1. *Flow of the system*

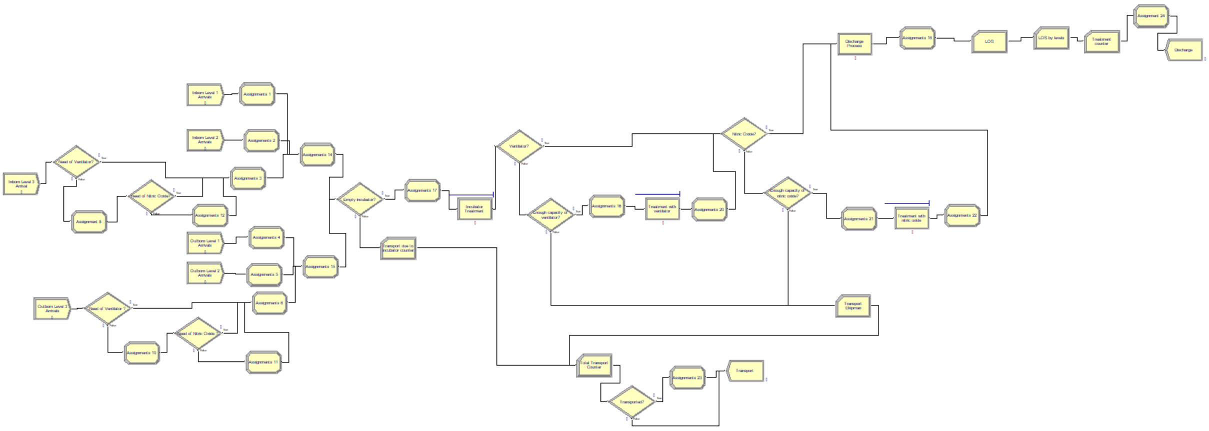

Figure 2. *ARENA model screenshot for the problem*

3.4. Output Analysis

Implementing the simulation model in real life to evaluate the simulation model results obtained in the study and comparing the results is a troublesome practice that is both time-consuming and costly. Simulation output analysis is conducted to determine whether the simulation model runs as intended and represents the real system. Therefore, some parameters related to the problem have been identified and evaluated to test the verification and validation of the simulation model.

The duration of the simulation should first be determined. In this context, the length of the simulation was identified as six years, as equipment planning requires long-term investment planning. Rejection and transport ratios and Levels 1, 2, and 3 LOS were selected as criteria for the evaluation of the performance of the simulation model.

Since the simulation model will be in the “zero” position at the beginning, a warm-up period should be determined, and the simulation should begin at the end of that period. This is important in terms of reflecting the actual system. In this study, the warm-up period, which is the period that lapses until the system achieves a stable status, was determined using the “Welch graphic method” [34] and the results for w = 20 days are presented in Figure 3. When the rejection and transport ratio, which is the first performance criteria, is analyzed (Figure 3a), the data is observed to move around the value 0.01 at the end of approximately 200 days. Moreover, the data is observed to move in narrower distances after 300 days for Level 1 LOS (Figure 3b), approximately 300 days for Level 2 LOS (Figure 3c), and approximately 300 days for Level 3 LOS (Figure 3d). Therefore, the warm-up period was selected to be 365 days.

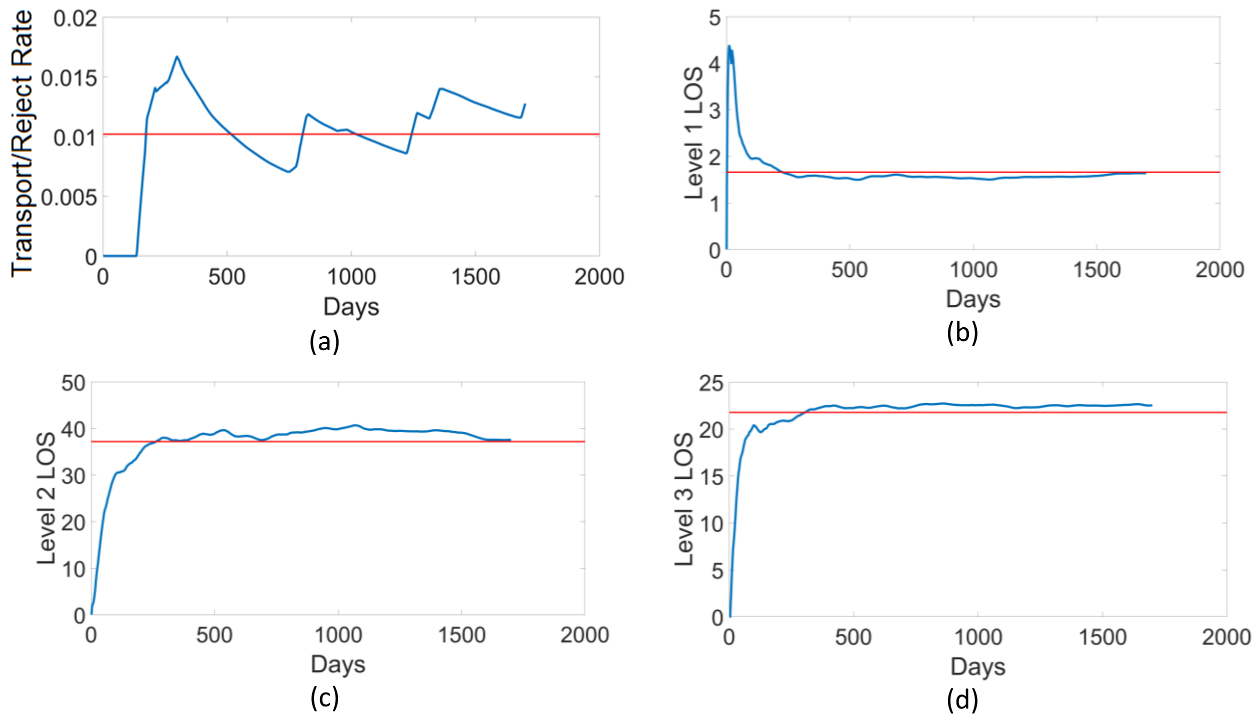

Figure 3. *Warm-up period calculation for all performance criteria*

The relative error approach, which is one of the fixed sample size methods, was used to determine the number of replications [35]. The final number of replications is determined by comparing the efficiency of the relative error value calculated by the relative error formula with the adjusted target relative error value. At the start of the application, preliminary replications should be performed. A minimum of 10 replications must be conducted at the beginning to determine the sufficient number of replications [36]. Both the significance level ($\propto$) value and the relative error (γ) value should be between 1% and 5% so that better results can be achieved [34, 35]. The number of replications can be calculated in three steps. In the first step, the initial number of replications is obtained from the simulation model. Following this, the relative error for i = n is calculated in the second step. Finally, i is incrementally increased to achieve a lower or equal calculated relative error.

Fifteen replications are performed in the initial replications, and the results obtained from these initial replications are provided in Table 3. The target relative error is selected as $\gamma = 0.1$, and the required replication number is selected as 75. According to the results, 4/5 performance criteria provide less than a $\gamma = 0.003$ level. Only the rejection and transport ratio has a 0.085 relative error value. Therefore, the number of replications is set to 75.

Table 3. *Results of the replications*

	Reject and Transport Ratios	**Level 1 LOS**	**Level 2 LOS**	**Level 3 LOS**	**Average LOS**
	(%)	(Days)	(Days)	(Days)	(Days)
Mean	1.217	4.160	14.705	22.544	14.152
Variance	0.203	0.001	0.017	0.115	0.028
Standard Deviation	0.450	0.038	0.130	0.340	0.167
N_0	15	15	15	15	15
Relative Error for 75 Replications	0.085	0.002	0.002	0.003	0.003

3.5. Optimization Model

Mathematical models that consider the parameters in the simulation model and target maximum resource utilization ratios, minimum rejection and transport ratios, and minimum inborn rejection and transport ratios to determine the optimal number of resources are recommended. OptQuest for ARENA software was used in the implementation of mathematical models, and applications were performed using an Intel Core i7 computer with 3.6 GHz and 16 GB RAM.

Sets and Parameters

Symbol	**Description**
i, k	Equipment type (*N*)
j	Patients (*M*)
t	Time periods (T)
z_j	1 if the j^th patient is inborn, 0 otherwise
h_{ij}	Treatment time of the j^th patient with i^th equipment
L_i	Lower bound of the capacity of i^th equipment type
U_i	Upper bound of the capacity of i^th equipment type
p_{ik}	Policy ratio that balances the number of the equipment type *i* and *k*
s_{ij}	Starting time of the j^th patient with the request of i^th equipment
T	Simulation length
Decision variables	
y_{ijt}	1 if the j^th patient is assigned to the i^th equipment at time t, 0 otherwise
r_{jt}	1 if the j^th patient is rejected or transported at time t, 0 otherwise
q_i	Capacity of i^th equipment type

The mathematical model is given as follows:

$$\max z_1 = \sum_i \sum_j \sum_t \frac{y_{ijt}}{T} \tag{1}$$

$$\min z_2 = \sum_t \sum_j \frac{r_{jt}}{M * T} \tag{2}$$

$$\min z_3 = \sum_t \sum_j \frac{r_{jt} * z_j}{M * T} \tag{3}$$

$$\sum_t y_{ijt} = h_{ij} \qquad \forall i, j \tag{4}$$

$$\sum_t t * y_{ijt} \geq s_{ij} \qquad \forall i, j \tag{5}$$

$$\sum_t t * y_{ijt} \leq s_{ij} + h_{ij} \qquad \forall i, j \tag{6}$$

$$y_{ijt} \leq 1 - r_{jt} \qquad \forall i, j, t \tag{7}$$

$$q_i \leq U_i \qquad \forall i \tag{8}$$

$$q_i \geq L_i \qquad \forall i \tag{9}$$

$$q_i \leq q_k * p_{ik} \qquad \forall i, k \; i \neq k \tag{10}$$

$$y_{ijt} \in \{0,1\}, \qquad r_{jt} \in \{0,1\} \qquad \forall i, j, t \tag{11}$$

The first model considers the first objective in Equation (1) that maximizes the total utilization ratio of all equipment during the simulation length. Furthermore, the object of the second model is given in Equation (2), which aims to minimize the rejection and transport ratios of all patients. Finally, the third model's objective function (Equation (3)) attempts to minimize the rejection and transport ratios for only inborn patients.

There are some constraints in the system for all models. The first constraint (4) forces the assigning of a patient to a required equipment during the treatment length. Meanwhile, the second and third constraints (5) and (6) are the scheduling constraints that ensure that the patient must be assigned to an equipment after the demand is reached (Equation (5)), and tapering of treatment is not allowed (Equation (6)). Constraint (7) ensures that a patient can only be assigned if the patient is not transported. Furthermore, constraints (8) and (9) provide the lower and upper bounds for each equipment type. Then, constraint (10) ensures capacity enforcement between equipment i and k. The equipment capacities must be balanced with one another regarding the p_{ik} values. Finally, constraint (11) enforces the valid ranges of the variables.

4. RESULTS

4.1. Simulation Model Validation

The total number of patients, number of discharged patients/deaths, number of patients rejected/transported, and simulation model outputs are obtained. The simulation results reveal that 1276±32.69 patients will arrive in the system during the planning horizon, of which 1260±24.79 will be discharged and 16±7.9 will be rejected or transported for all replications.

The validation of the system with the real system is performed using a statistical t-test for performance criteria. The LOS for each level is summarized in Table 4 for randomly selected observations and simulation results. According to the results, 122,814 patients were analyzed as Level 1 during the 75 replications. The mean values of the observed and simulated patients appear to be quite close, while the standard deviation values may differ. This is reasonable when the number of patients in the simulation system is considered. p-values from the test statistics are calculated as 0.61, which is higher than the 0.05 confidence level. Similar results are obtained for the LOS values of Level 2 and Level 3 patients.

Table 4. *Validation of the model*

	# of selected observed patients	Mean of observed patients	Std. dev. of observed patients	# of simulated patients	Mean of simulated patients	Std. dev. of simulated patients	p-value
Level 1 LOS	77	4.08	5.58	122,814	4.16	1.45	0.61
Level 2 LOS	305	8.58	5.48	180,141	8.65	3.54	0.74
Level 3 LOS	97	19.11	14.69	116,717	19.78	11.62	0.57

4.2. Results

The results obtained for three optimization models created for three different objective functions are presented in this section. Each of the optimization models' results and the current system model were compared with the performance criteria, and the results are summarized in Table 5. A reduction of the quantities of all resources was found to be necessary to maximize the usage rates of all equipment. According to the results obtained, occupancy rates for incubators increased considerably compared with the current situation, but the same level of increase was not identified in other resources. In this scenario, it was recommended that nitric oxide treatment should not be performed. With respect to the desire for the minimization of rejected and transported ratios, on the other hand, it appeared that all resources available should be open for the minimization of all rejected and transported ratios, including those of inborn patients. In this way, for instance occupancy rates for the incubator were decreased to 65.78% from 75.6%, and the rejected and transported ratios were reduced to 0.0008 from 0.012.

Table 5. *Optimization results*

Parameters		***Objectives***			
		Current system's simulation results	**Maximum utilization of equipment (z_1)**	**Minimum reject and transport ratio (z_2)**	**Minimum inborn rejection (z_3)**
Decision Variables	*# of incubators* (q_1)	66	50	75	75
	# of ventilators (q_2)	30	20	40	40
	# of nitric oxide (q_3)	1	0	5	5
	Reject and transport ratio ($\sum\sum r_{jt}/M$)	0.012	0.338	0.00086	0.000862
Outputs	*Utilization of incubators (%)*	75.6	95.3	65.78	65.78
	Utilization of ventilators (%)	5	4	3.1	3.1
	Utilization of nitric oxide (%)	4.1	0	1.1	1.1
	Rejection and transport ratio (%)	1.227	33.77	8.62	8.62
	LOS (days)	14.1187	14.0244	14.1252	14.1252

The optimization results for the three objectives should be consolidated. Therefore, an experimental design is considered, and each model's results and the current system are used for distribution fitting. According to the methodology, each resource capacity is fixed considering all three objectives. First, the optimal number of incubators required for all objectives was determined by considering the curves and the current situation. The curves concern the rejection and transportation rates as a performance criterion. The curve formed for determining the number of incubators is presented in Figure 4. The point at which the curve will achieve the minimum value for the reject and transport rate is observed to be 72. Accordingly, the optimal number of incubators for all objectives was determined to be 72.

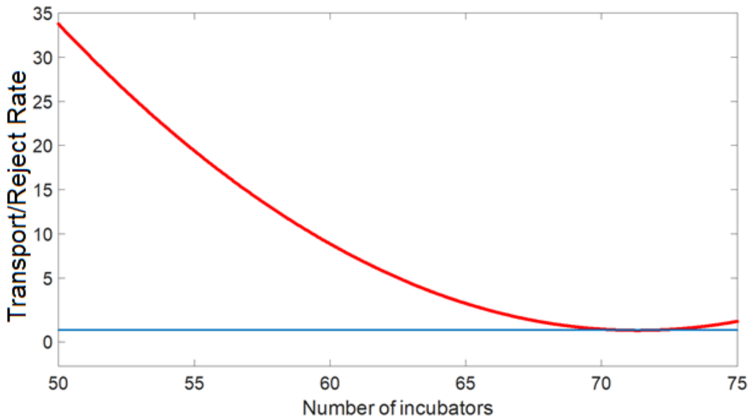

Figure 4. *Optimal number of incubators regarding rejection and transport rate*

Similar to the determination of the optimal number of incubators, a curve is fitted regarding the results from the optimization models and the current system. The optimal number is observed to be 35 regarding the number of ventilators. Accordingly, it was observed that the employment of 35 ventilators was required to achieve the lowest rejection and transport ratios considering all objectives (Figure 5).

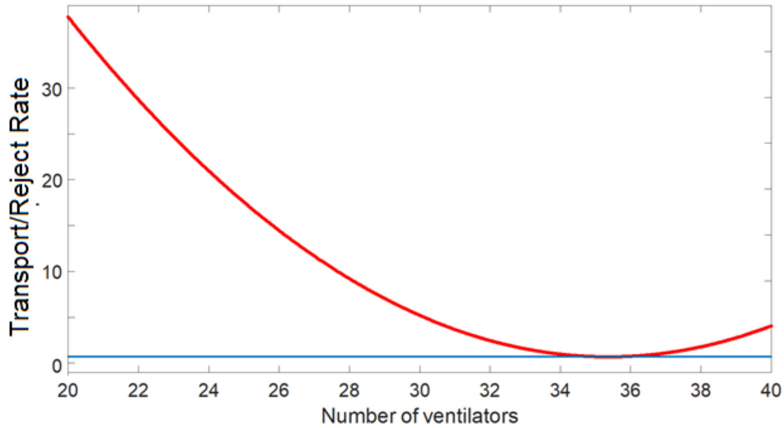

Figure 5. *Optimal number of ventilators regarding rejected and transported rate*

Finally, in view of nitric oxide devices, it is observed that three devices will ensure the achievement of the lowest rejected and transported ratios. This indicates that the inclusion of two new nitric oxide devices in the system will yield more effective results, as seen in Figure 6.

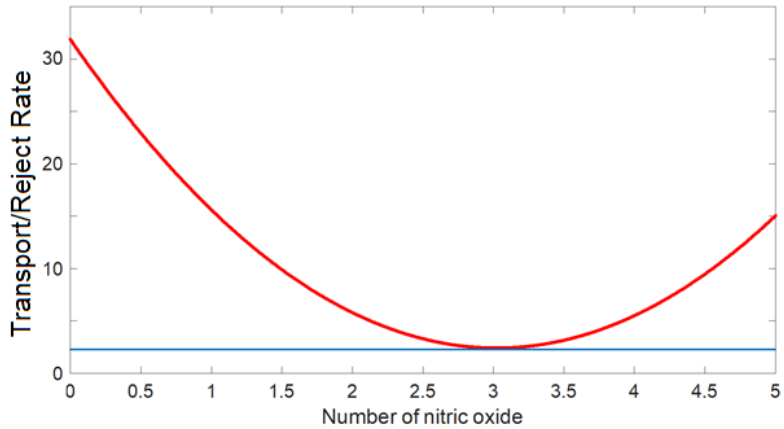

Figure 6. *Optimal number of nitric oxide devices regarding rejected and transported rate*

After the analysis of the optimization models and the curve fitting study applied afterward, the simulation model was run again according to the number of incubators, ventilators, and nitric oxide devices obtained from the curves. Table 6 displays this best allocation of the model for considering three objectives together. According to the improved system, the number of incubators is set to 72, the number of ventilator devices is set to 35, and the number of nitric oxide devices is set to 3. Based on the findings of the best system compared with the single objective results provided in Table 5, more suitable utilizations and rejection and transport ratios are obtained. The rejection and transport ratio is nearly 0, and rejections caused only by a lack of incubators in the improved system. It can be concluded from the system that more utilized resource allocation compared with the minimum rejection and transport ratio and minimum inborn rejection ratio objectives is obtained, but utilizations are quite reasonable in the improved system. LOS values are not changed, and it is clear that the system does not permit queues.

Table 6. *Results of the optimal allocation*

Parameters	Current System	Best system
Utilization of incubators (%)	75.6	68.4
Utilization of ventilators (%)	5	3.5
Utilization of nitric oxide (%)	4.1	1.7
Rejection and transport ratio (%)	1.228	0.002
LOS (days)	14.1187	14.1248

5. CONCLUSION

In this study, a simulation-optimization model for determining the optimal quantities of each equipment in the case of a patient profile with inborn and transported patients from different levels in a NICU was recommended. First, the existing system was modeled, the equipment occupancy and capacity status were evaluated, and the number of incubators, ventilators, and nitric oxide devices required for maximum occupancy was found.

In the present case, the reject and transport rate is approximately 1.5%, and the number of incubators, ventilators, and nitric oxide devices required to minimize this rejection and transport rate has been determined. Finally, it was aimed to minimize the rate of transplantation for inborn patients, and the optimal quantities of each equipment required to do so was determined. To minimize inborn transport, the quantities of each equipment required was determined, in addition to the quantities of each equipment that the hospital management should possess while establishing an acceptance and rejection and transportation policy for inborn and outborn patients.

Accordingly, the simulation-optimization model was run for three different purposes, and ideal results were obtained. Bottlenecks in the patient admission and treatment process were identified with the use of this simulation model. An optimization model has been proposed to improve the current system, make long- and short-term capacity planning, and determine the effects of changes to be made in terms of patients and cost.

Using the approach proposed in this study, optimal equipment planning will be performed for different purposes. The limitations of this study are that the decisions are made for a particular hospital, there is no planning throughout the city, and specific equipment is included in the system.

In addition, in the proposed approach, treatment and arrival times according to the diseases were not examined, and it was deemed appropriate to examine according to the levels. Therefore, the proposed model can be expanded for systems with different equipment and resources, as this serves as a guide in making administrative decisions. Furthermore, a model can be used for systems related to different patient arrivals and treatment distributions. Finally, the model can be transformed into a decision support system, and software that can offer input to health policymakers can be created.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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