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Workflow-based Adaptive Layout Design to Improve the Patient Flow in theOutpatient Clinics

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ABSTRACT

The performance of outpatient clinics is measured through waiting times and resource utilization and the reasons for low performance is often viewed as operations issues: planning, scheduling and coordination between resources and patients. In this study, we show that layout design also contributes towards operations management. Here we propose workflow-based layout design that obtains optimal layout design by incorporating patient workflow and its related flow/precedence constraints so that performance parameters are improved. For this, we modify the Ant agent algorithm. Performance parameters of the existing and optimal layout are compared. Ant agent algorithm provides the best solution that minimizes the waiting time and cycle time. Layout design or redesign that is based on workflow and precedence constraints improves the patient flow in the outpatient clinics.

KEYWORDS

Layout Optimization, Patient flow, Ant Agent Algorithm, Waiting Time, Workflow Management.

Introduction

Long waiting times pose greater challenge to operations management in Outpatient Clinics (OPCs). The reason for the problems to arise in workflow management is due to lack of effective planning[1], scheduling [2] and coordination of patients and resources [3]. OPCs are not only about the patients and resources (staff and equipment) but also a collection of different service providing departments (physical locations with boundaries). The OPC layout designs affect the workflows therefore contributing towards the patient waiting time, resources utilization and efficiency of the clinics. The OPC's layout design and the allocations of the locations (rooms) to the departments impact either positively or negatively on the operations management/workflow management.

Outpatient clinics are complex networks with interconnected and interrelated services. The functional organization structure of the OPCs make the patients to move from one department to another in order to complete his/her treatment processes. Patients have to travel or walk around to different departments (locations/rooms) and this adds to the time patients spend (cycle time) in the clinic. Generally, the hospital/OPC building are designed with architectural point of view and that might match with its current demand trends but over a period of time when demand increases, OPCs would get congested resulting in workflow chaos. This would lead to compromise in efficiency. Therefore, the OPC layout design along with architectural point of view should incorporate the operations management point of view.

In the literature, it is observed that layout optimization is commonly addressed in manufacturing industries, VLSI chip designs, chemical plants etc. Facility layout problems (FLP) are basically the allocation problems with constraints. Heuristic and meta-heuristic algorithms are used to solve the FLP. The layout optimization has been commonly modelled as Quadratic Assignment Problem (QAP). The way the new and existing layouts are optimized differ as the latter have greater number of constraints compared to new layouts. In this paper, we obtain an optimal layout design for OPC to improve the patient flow, thereby incorporating the workflow operations management perspective in layout redesign.

This paper is organized as follows: Section 2 presents the literature review, Section 3 details the materials and methods: data collection and analysis, model development and validation, and experimental designs followed by the proposed Workflow based Adaptive Layout Design. Results and Discussion are presented in Section 4 and Section 5 presentsconclusion.

Literature Review

Generally, architects plan the hospital buildings on a long-term perspective based on their experience, design aspects and legal regulations. Consequently, at a strategic level, hospital layout planning can be classified as resource/capacity planning [4]. However, at operational level, the layout has its influence on the quality of healthcare services provided in the clinic [5]. The hospital's strategic decisions are related to future development with the time horizon of 1-5 years whereas the hospital building remains for more than that time. Therefore, the layout of the hospital should be designed carefully so that it can adapt to the future changes in the workflows. The hospital building design needs to be evaluated from operations management viewpoint/perspective to assure that the building design supports the effective and efficient workflow of care processes, in current situation as well as in the future when the patient demand increases. Hospital layout necessarily needs to be suitable in order to deal with all the types of flows like patient flow, materials flow, staff flow and information flows. After all, the layout design is a strategic decision which is a long-term decision and layout cannot be adapted very easily for changing scenarios and such changes involve high cost. It's a challenging task to design hospital layout that incorporates the uncertainties and future patient demand and related technologies. The authors in [6] have described the relationship between the operations management and the hospital design. From an architectural point of view, hospital consist of static locations like consultation rooms, corridors, examination rooms, waiting facilities, reception desks, laboratories, diagnostic centers, operation theatres etcetera. From the view of operations management, hospital is a system in which all locations are related to each other. Patients, staff (doctors and nurses) and information move from one location to another. A logistic system has to control and support the hospital's operations.

Over time the original layout of a hospital may become unsuitable due to the changes in the number of patients, the types of patients, case mix and the surrounding environment. Therefore, the layout should be reviewed for possible changes to improve the patient flow. The layout based on the current demand will be unsuitable as and when the demand change. The hospitals add facilities when they expand and this addition of the new facilities creates/ increases the number of workflows and also the dependencies among the departments. Simulation is an important method to analyze the optimal layout. This is due to the cost involved in altering the hospital layout. Therefore simulation gives best possible layout in different type of situations/scenarios [7, 8].

The layout optimization problems have gained a lot of importance in the recent times. The layout can be simulated according to the hospital type and patient type and demand. Various design options can be simulated and the optimal design can be chosen. But when optimizing (redesigning) the layout based on the workflow for the existing hospital, there exist a greater number of constraints. The existing layouts itself impose limitation for the redesign.Layout design of hospitals is most relevant to achieve better performance in hospitals where logistic flows are structured and managed during the process of planning[9]. The parametric model of layout design optimizes the performance along with other parameter of interest. The parametric model is also applicable to hospitals, as it utilizes a geometric approach that helps in handling the complexities that arise because of predefined rules and parameters and precedencies. The performance-based parametric model is applicable for design problems that are concerned with designing of complex layout with many different pre-requisites and preferences as per existing hospitals. The topology of hospital building focuses on functionalities like treatment, care, diagnostics, waiting times, reduce waste and workload. That is because of the complexity involved in the topology and such design approach is used in order to achieve high performance in the parameter of interest. [10].

Architectural layout design finds association with space syntax. It deals with space and human behavior and it has been widely used for analyzing buildings. It is observed that its utilization in hospitals has been comparatively less. Most of the research studies that have used space syntax theory are in inpatient setting for studying the nurse movement patterns. It explored the way the nurses change their behavior as per the environment in which they work. The mentioned study tests the space syntax theory and technique and their relevance on logistic system (flow and path)[11]. Yet no much of research has been conducted to study spatial layout design/redesign with the goal of improving operational efficiency [12]. Recently, a study was carried out using discrete event simulation tool for hospital space planning that incorporated patient and doctors' information and waiting times. It defines space requirements based on these parameters [13].

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The distance between the departments and the movement of materials and staff in the hospital has impact on patient cycle time and efficiency. The distance between the departments will increase the resource/patient switching time which results in non-value adding activity. This increases the cycle time of the patients and reduces the utilization. Hospitals along with providing health related activities, they also create and constrict them. The time taken for the patients to locate and go to the required consultation room increases the cycle time of the patient. The location of consultation rooms and the travelling time of doctors and patient play an important role in the workflow optimization[14].

The hospital is a network of interactions comprising of functional structures, care processes, and outcomes. The workflow is optimized either optimizing any of these parameters or in combinations of these parameters. The authors in [15] examine the effect of structural adjustment (change in layout) and process improvement (patient pathways implementation) on performance of emergency room (ER) operations. The authors implemented a structure-oriented approach in improving its ER operations in one hospital and employed a process-oriented approach in another hospital. To analyze the improvements, the data was collected, before and after the planned changes were implemented at each hospital. The Statistical analysis showed that process-oriented implementation had more positive impact on performance than the structure-oriented implementation but the process optimization involved extensive employee training. It is beneficial for hospitals to combine both structure-oriented and process-oriented strategies in order to maximize their performance.

The layout optimization at the basic level is assigning locations to the facilities, and these are commonly modelled as Quadratic Assignment Problem (QAP) [16, 17]. The first fitness function analyzed is the distance correlation between the facilities and locations. Usually branch and bound techniques are used to achieve this. The layout optimization is a step-by-step design process. It involves observing and analyzing the current available space, correlation between facilities and processes. Then with an objective function obtain the layout to achieve the objective. Evaluate the layout designs with current layout in terms of feasibility, cost, patient safety, flexibility. Distance and resource utilization [18]. From the literature it is observed that the layout problems are solved using different methodologies: (a) Exact procedure (b) Heuristics (c) Meta heuristics. The exact procedure uses branch and bound methods. Heuristics use the algorithms which are either distance based or adjacency based. The layout optimization is carried out in two ways; one construction type and other improvement type [17]. The constructive type uses the rules of thumb. This type builds a solution from scratch and it uses decision process of *n*-stage. Sometimes these rules are automated in order to make assignments that are intelligent, at each stage. The improvement type optimization starts with a single solution and incrementally improves it. It begins with an initial solution, systematically evaluates the possible solutions and makes an exchange if it improves the value of the criterion. Currently, extensively used Meta-heuristics are simulated annealing, genetic algorithm and ant agent algorithms. These solve large scale Facility layout problems. Other approaches for layout optimization are neural network, fuzzy logic and expert system [8, 17, 19, 20]. Dorigo invented the Ant Colony Optimization (ACO) method for Travelling Salesman Problem [21]. The ants move throughout the network and find the shortest path from source to destination. The ACO is inspired by the biological ants which find the shortest path when searching their food. A chemical substance called pheromone is deposited by the ants which helps the other ants to coordinate and follow the shortest path. ACO has many applications in wireless networks, traffic controls and also facility layout problems in manufacturing industries [22-24]. ACO is a combinatorial algorithm and it has been used in designing intelligent systems. Ant agent algorithm is efficient and effective in scheduling of patients in real time and achieving continuous patient flow in outpatient clinics[2, 3, 25].

In this study, the layout design obtained considers the variability and uncertainty in the patient volume and arrival times, the workflow paths and department dependencies as well as the physical constraints. The literature shows that the optimal layout design obtained using various techniques and algorithms do not incorporate the workflow paths and the constraints. Therefore, this research implements intelligent algorithm to obtain optimal design so that the layout design can be implemented to new as well as existing clinics.

Materials and Methods

This study was conducted in OPC of Aravind Eye Hospital (AEH), Madurai, Tamilnadu, India. It receives around 2300 patients/day that too only walk-in patients. All the patients are provided the quality care on the same day. As all are walk-in patients that is patient arrivals is random, it creates a lot of variability and uncertainty making the workflow management complex. The patient volume and patient arrival times are independent variables that affects the dependent variables like cycle time and waiting time. The waiting time and the cycle time depend on the processing times and the patient arrival pattern and are controlled by the scheduling rules. The locations of the departments, the seating capacity of the waiting rooms, the distance between the departments, the precedence constraints among the departments were collected. The simulation model was developed based on the OPC workflow and the physical locations in the layout. The input was modelled through analysis of the collected data and the output was measured. The details regarding the data collection and analysis are described later in this section. The developed simulation model was validated with the existing hospital workflow. The intervention was the optimal assignment of the locations to the departments in the outpatient clinic. The proposed layout optimization model with Ant agent algorithm was run. The OPC workflow with the obtained layouts were simulated to observe the performance parameters like waiting time, cycle time, walking distance for patients and resources.

Data Collection and Analysis

The elementary data collection was carried out through interviews with hospital staff of AEH so as to understand the workflow of the hospital. The hospital uses IHMS and CMS (hospital information management system) from which the patient and process data were collected. Two months data such as patient demand, arrival times, in-time and out-time of patients and resources, resource schedule and load distribution in both units were collected. The waiting times, cycle times, patient mix, reaction times, service times, and utilization were extracted from the collected data [2]. A data fitting tool: Easy-Fit was used to determine the probability distributions of service time and patient arrival time. It was observed that through data analysis that the patient arrival pattern had two peaks, at around 8 am and 10 am. Therefore, a bimodal Poisson distribution [26, 27] was selected to generate model arrival timesThe OPC under study is situated on the ground floor along with registration (new and review separately), pharmacy, optical lens, counselling unit. The floor layout is as shown in Figure1. The physical dimensions of the OPC were collected from the administrative office. The distance between the locations was measured by the human steps (walking) which later translated to time in the simulation. The time taken to walk distance varied and the number of steps also varied based on the age and height of the patient respectively. Therefore, 10 staffs were employed to measure the number of steps between the locations for 10 times. The average numbers of steps were taken for simulation. The walking style or the pattern of the disabled patients was excluded as they contributed less than 1% of the patient volume. After registration, few patients opt to have refreshments before proceeding with the diagnostics and such patient's data were excluded.

The other input information like wait time, patient mix and service time were extracted from the collected data. The process data of a total of 20392 patients was obtained and 2707 samples of them were excluded as the recorded cycle time was less than 20 minutes. The minimum time spent by patients for basic and simple routine without any waiting was not less than 20 minutes. Therefore, the remaining 17685 samples were used to build the model. The probability distribution of service time and patient arrival time was determined by EasyFit, a tool used for data fitting. The goodness of fit test was conducted using Kolmogorov-Smirnov test. The Poisson distribution with a peak load of 200 patients at 10 am was selected for generating patient arrival times and later calibrated to Poisson distribution with two peaks: 8 am (150 patients) and 10 am (200 patients) (based on empirical data). Therefore, a bimodal Poisson distribution was selected to generate patient arrival times.

The processing time was fixed to average value for all the departments in the simulation. The simulation model was calibrated by changing the fixed processing time to variable processing time which was derived from the empirical distribution. Service times were uniformly distributed between the minimum and maximum processing times from empirical data for each department and were randomly generated. Walking steps were uniformly distributed between the minimum and maximum walking steps from data collected for each department and were randomly generated. The operations managers were asked to verify and validate the model. We exclude the resource and patient scheduling methods as we do not modify them in this research.

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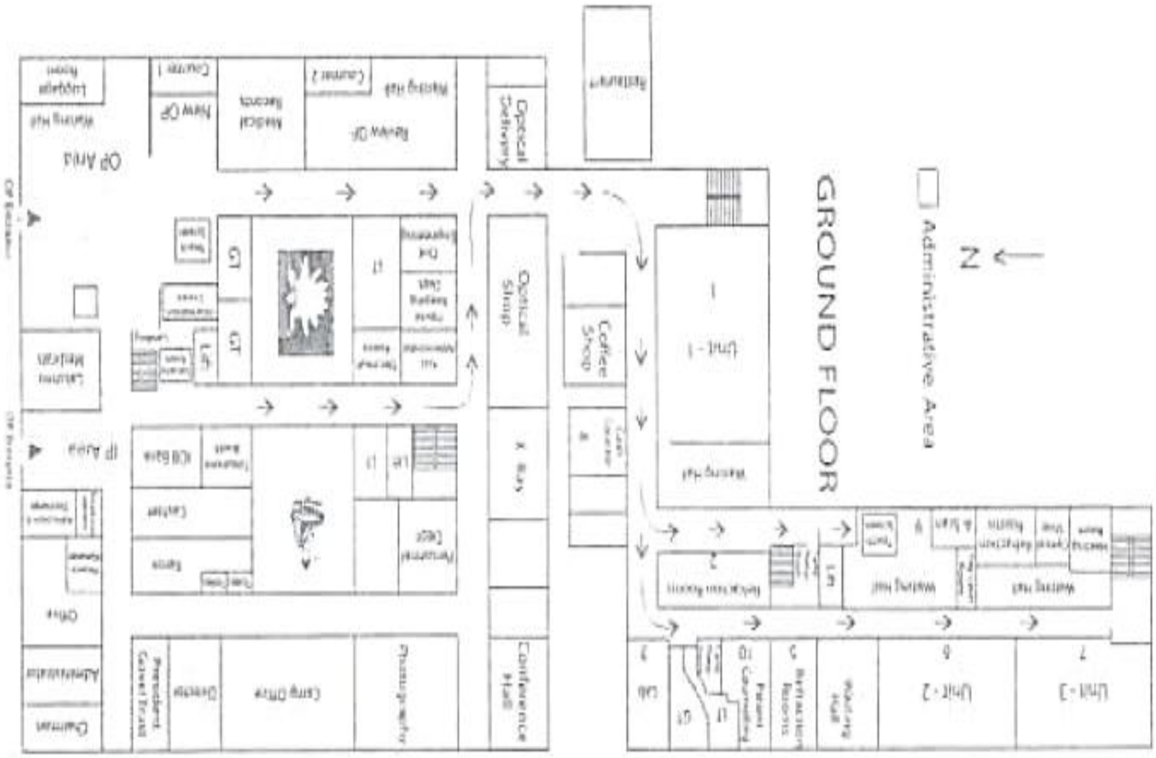
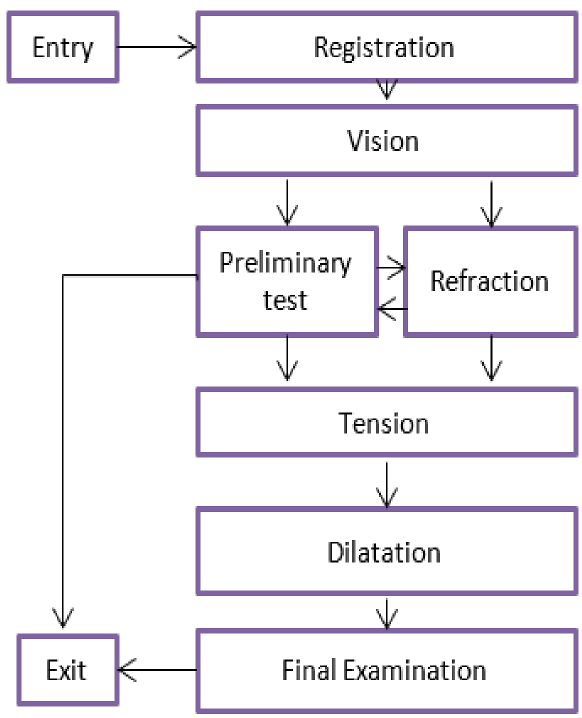


(a) Layout diagram of Aravind Eye hospital OPC



(b) Outpatient clinic workflow of Aravind Eye hospital

Fig. 1

Model Development

The discrete process based stochastic simulation model was developed using Microsoft's .NET Framework. The progress of patients and resources was tracked throughout the OPC. The model was constructed on the predefined operations logistics such as type of patient, pathways/flow, departments, resources/staff and the distance between the departments. The processing times, arrival times (in-time) and exit times (out time) were used to build the system. Walking steps were uniformly distributed between the minimum and maximum walking steps from data collected for each department and were randomly generated. The operations managers were asked to verify the model. The simulation model was run with the empirical data and the performance measures, namely, waiting times, cycle times, utilization and load distribution, were collected. The results of the simulation model were compared with the empirical data of the OPC for validation as shown in Table 1 and there was no statistical difference between the two.

Table 1. Validation of waiting time and cycle time between simulated results and empirical data

	Empirical data		**Simulation results**		**P value**
	Mean	**S.D.**	**Mean**	**S.D.**	
Wait time in minutes	59.5	43.92	58.2	40.15	0.4
Cycle time in minutes	113.26	44.2	115.32	39.6	0.29

Experimental Design

The layout redesigns were obtained with the proposed model. Two scenarios were simulated: first with existing layout and second with the optimal layout. the same input data was used for both scenarios: same patient demand, mean arrivals, and patterns of arrivals. The Random Variate with different seed value was used to generate various input data sets. ANOVA test was performed for statistical comparisons at significance level of 0.05 α value on the mean of output performance indicators before and after intervention.

Workflow-based Adaptive Layout Design Optimization

The layout optimization of the existing outpatient clinics becomes more difficult as it would have a greater number of constraints like space, workflow, patient flow, resources and logistic flows. The objective of OPC layout optimization is to minimize the walking distance (travel time) of the patients and resources which in turn would reduce the waiting time (non-value adding tasks). The problem formulation of the OPC based on process flow and dependencies, distance between locations and adjacency between the locations is presented in Equation 1.

$$\text{Min } \sum_{i=1}^{N}\sum_{j=1}^{M} F_{i,j}\, D_{i,j}\, N_{i,j}\, X_{i,j} \tag{1}$$

Where $F_{i,j}$ is the flow matrix which gives the process flow of the patients
$D_{i,j}$ is the distance matrix between the locations (here the distance is represented innumber of footsteps)
$N_{i,j}$ is the neighborhood matrix of locations
$X_{i,j}$ =1
M is the number of departments
N is the number of locations
$M \leq N$
We solve this optimization problem with few modifications to the Ant agent algorithms. Later, the resultant layout and performance parameters like waiting time and cycle time are compared with existing ones.

- **Ant Agent Algorithm for FLP of OPC**

The Ant Agent algorithm is a bio-inspired algorithm. A single ant has very limited ability, but, through cooperation, the colony can perform very complex tasks. When an ant moves on a path, it deposits pheromone (a chemical signalling molecule) on the ground. The other ants follow the (perhaps many) paths defined by the pheromone, where the path with the strongest concentration of pheromone is more likely to be chosen. Because the ants on the shorter path return more quickly, then the pheromone on the shorter path is reinforced and as a result it will attract more ants again. This is a positive feedback loop, which quickly leads to the emergence of a shortest path [28, 29]. The Ant algorithm was modified by incorporating the precedence constraints so that the departments are allotted

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nearby locations as per the tasks in the sequence, wherever possible. Numbers of ants are generated from the source. Each ant traverses through the locations to obtain the shortest walking distance with the predefined constraints. When ants reach the destination, the ant with minimum walking distance is selected and the corresponding layout is selected. The modified algorithm based on workflow constraints is presented below.

{
Initialize the parameters and the pheromone trail.
For (iteration = 1 to MAX)
{
For (ant k=1 to m)
While (any location is not visited by k)
Determine next location with probability p_{ij} as defined by

$$p_{ij} = \max \frac{\tau_{ij} . \eta_{ij}}{\Sigma \tau_{ij} . \eta_{ij}} \tag{2}$$

where p_{ij} is the probability of an ant in node 'i' selecting location 'j' $\forall j \in F(i)$, τ_{ij} is the pheromone value on the arc i,j and η_{ij} is the heuristic information guiding the ants.

Update the pheromone on the walked paths by

$$\tau(i,j) = (1\text{-}\alpha).\ \tau(i,j) + \alpha.\tau_0 \tag{3}$$

where $\tau(i,j)$ is the pheromone value on the arc connecting location 'i' to location ' j'. α is the evaporation rate at which the pheromone evaporates ($0<\alpha<1$). The evaporation rate plays an important role in the routing. It impacts the load balancing in the network. τ_0 is the initial pheromone value at the start of the algorithm.

$$\tau_{ij} = (1\text{-}\alpha).\tau_{ij} + \alpha/T_{best} \tag{4}$$

where T_{best} is the best shortest distance layout with all precedence constraints.

}
Output is the best layout and other data
}

The optimal solution obtained by the Ant agent algorithm was saved in the database. Output the solution with minimum distance. There are 12 locations in the OPC therefore the number of steps = n (n-1)/2=12*11/2 = 66 steps.

Results & Discussions

The simulation model of the OPC and the algorithms to find the optimal layout was developed in .Net (Dot net). The best layout solution from the proposed model and algorithm was integrated in the simulation model and the impact of the physical layout on the performance parameters like waiting time and the cycle time were observed. The layout was optimized based on the travelling time (distance) from entry to exit of the OPC. The ant agent algorithm provides the optimal layout as solution. The optimal layout design provided by the proposed method will have a smaller number of walking steps considering the workflow of patients. In this particular layout, the distance is 211 steps for optimal layout as compared to the prior situation of 295 steps.

The performance or the efficiency of the OPC depends on the processing time, waiting time, cycle time, throughput, resource utilization and operational costs. The waiting time and the cycle time also depend on the resource utilization (in this research, it is the space utilization). After the simulation was run the solutions obtained from the algorithm are exported to excel sheets to compare the performance. The waiting time and the cycle times for the OPC layout with minimum distance and the existing layout are compared in Table 2. The ANOVA test ($p<0.05$) was used for statistical significance analysis.

Table 2. Comparison of wait time and cycle time in existing layout and optimized layout

	With existing layout	**With optimal layout**
Wait time in minutes	59.5	50.2
Cycle time in minutes	113.26	101.54

The results show that the physical layout of the outpatient clinic has impact on the workflow management: patient flow, wait time and cycle time. The wait time have reduced by and 15.6% (9.3 minutes) and the cycle time reduced by 10.34% (11.72 minutes). The staff scheduling and the patient scheduling was same as of the existing OPC workflow management. The optimal solution obtained resulted with reduction in walking distance by 295 to 211.

The Ant algorithm provides the single best optimal solution for the layout with the objective of minimizing the walking distance which contributes to the cycle time of the patient. The layout obtained by the Ant algorithm required changes to the existing layout (moving the equipment like refractometers to other locations). The cost of the equipment movement was not estimated in the model. It would be beneficial or easily implemented for new hospitals as the equipment could be moved easily. This is the limitation of this algorithm. We require sub-optimal solutions that would be implemented in existing buildings easily. With this size of layout problem, the execution time for Ant algorithm was 20 seconds. With the increase in number of locations, workflow precedence constraints and department or treatment complexities, the search space becomes wider and execution time will increase.

Conclusion

The physical layout of the Outpatient clinic has impact on its patient flow, cycle time, waiting time and resource utilization and this paper demonstrates it. In this study, we modified Ant agent algorithm for the layout optimization problem. Ant agent algorithm provided the best solution (only one solution which would be ideal in case of some scenarios particularly new hospital buildings). The model can further be extended to any type of hospital layout based on the practical feasibility analysis. Further the waiting time can be reduced by implementing space syntax in layout optimization.

References

[1] Tompkins, J.A., White, J.A., Bozer, Y.A., & Tanchoco, J.M.A. (2010). *Facilities planning*. John Wiley & Sons..

[2] McDowell, A.L., & Huang, Y.L. (2012). Selecting a pharmacy layout design using a weighted scoring system. *American Journal of Health-System Pharmacy*, *69*(9), 796-804.

[3] Kulkarni, C.N., Talib, M.I., & Jahagirdar, R.S. (2013). Simulation methodology for facility layout problems. *The International Journal of Engineering*, *2*(2), 24-30.

[4] Cubukcuoglu, C., Nourian, P., Sariyildiz, I.S., & Tasgetiren, M.F. (2020). A discrete event simulation procedure for validating programs of requirements: The case of hospital space planning. *SoftwareX*, *12*, 100539.https://doi.org/10.1016/j.softx.2020.100539

[5] Dimitris Karlis, E.X. (2005). Mixed Poisson Distributions. *International Statistical Review*, *73*(1), 35-58.

[6] Gambardella, L.M., & Dorigo, M. (2000). An Ant Colony System Hybridized with a New Local Search for the Sequential Ordering Problem. *Informs Journal on Computing*, *12*(3), 237-255.

[7] Hahn, P.M., & Krarup, J. (2001). A hospital facility layout problem finally solved. *Journal of Intelligent Manufacturing*, *12*(5-6), 487-496. https://doi.org/10.1023/a:1012252420779

[8] Hani, Y., Amodeo, L., Yalaoui, F., & Chen, H. (2007). Ant colony optimization for solving an industrial layout problem. *European Journal of Operational Research*, *183*, 633–642.

[9] Holst, M.K., Kirkegaard, P.H., & Christoffersen, L.D. (2013). Parametric Optimization of Hospital Design. *World Academy of Science, Engineering and Technology, 76*, 200-208.

[10] Hulshof, P.J.H., Boucherie, R.J., Essen, J.T.V., Hans, E.W., Hurink, J.L., Kortbeek, N., Litvak, N., Vanberkel, P.T., Veen, E.V.D., Veltman, B., Vliegen, I.M.H., & Zonderland, M.E. (2011). ORchestra: an online reference database of OR/MS literature in health care. *Health Care Management Science, 14*, 383-384. https://doi.org/10.1007/s10729-011-9169-4

[11] Hwang, T.G., Lee, Y., & Shin, H. (2011). Structure-oriented versus process-oriented approach to enhance efficiency for emergency room operations: what lessons can we learn?. *Journal of Healthcare Management,56*(4), 255-267.

[12] Boucherie, R.J., Hans, E.W., & Hartmann, T. (2012). Health care logistics and space: accounting for the physical build environment. *In Proceedings of the 2012 Winter Simulation Conference (WSC)*, 1-8.

[13] Khan, N. (2012). *Analyzing Patient Flow: reviewing literature to understand the contribution of space syntax to improve operational efficiency in healthcare settings.* Proceedings:Eighth International Space Syntax Symposium, Santiago de Chile.

[14] Kim, Y., & Lee, H.W. (2010). Analysing User Costs In A Hospital: Methodological Implicationof Space Syntax to Support Whole-Life Target Value Design. *Lean Construction Journal*, 55-65.

[15] Lee, H.Y. (2012). Integrating Simulation and Ant Colony Optimization to Improve the Service Facility Layout in a Station. *Journal of Computing in Civil Engineering, 26*, 259-269.
[16] Li, J., & Zha, H. (2006). Two-way Poisson mixture models for simultaneous document classification and word clustering. *Computational Statistics & Data Analysis, 50*(1), 163-180. https://doi.org/10.1016/j.csda.2004.07.013
[17] Liggett, R.S. (2000). Automated facilities layout: past, present and future. *Automation in Construction, 9*, 197-215.
[18] Dorigo, M., & Gambardella, L.M. (1997). Ant colony system: a cooperative learning approach to the traveling salesman problem. *IEEE Transactions on evolutionary computation*, *1*(1), 53-66.
[19] Munavalli, J.R., Boersma, H.J., Rao, S.V., &Van Merode, G.G. (2021). Real-Time Capacity Management and Patient Flow Optimization in Hospitals Using AI Methods. In M. Masmoudi, B. Jarboui, & P. Siarry (Eds.), *Artificial Intelligence and Data Mining in Healthcare*. Cham: Springer International Publishing, 55-69.
[20] Munavalli, J.R., Rao, S.V., Srinivasan, A., Manjunath, U., &Van Merode, G.G. (2017). A Robust Predictive Resource Planning under Demand Uncertainty to Improve Waiting Times in Outpatient Clinics. *Journal of Health Management*, *19*(4), 563-583. https://doi.org/10.1177/0972063417727627
[21] Munavalli, J.R., Rao, S.V., Srinivasan, A., & van Merode, G. (2020). An intelligent real-time scheduler for out-patient clinics: A multi-agent system model. *Health Informatics Journal*, *26*(4), 2383-2406. https://doi.org/10.1177/1460458220905380
[22] Munavalli, J.R., Rao, S.V., Srinivasan, A., &Van Merode, G.G. (2020). Integral patient scheduling in outpatient clinics under demand uncertainty to minimize patient waiting times. *Health Informatics Journal*, *26*(1), 435-448. https://doi.org/10.1177/1460458219832044
[23] Rajkumar, R., & Iyengar, N.C.S.N. (2012). JXTA: A technology facilitating mobile p2p health management system. *Osong public health and research perspectives*, *3*(3), 165-169. https://doi.org/10.1016/j.phrp.2012.04.008
[24] Rezaei, G., Afshar, M.H., & Rohani, M. (2014). Layout optimization of looped networks by constrained ant colony optimisation algorithm. *advances in engineering software*, *70*, 123-133.https://doi.org/10.1016/j.advengsoft.2014.01.009
[25] Singh, S.P., & Sharma, R.R. (2006). A review of different approaches to the facility layout problems. *The International Journal of Advanced Manufacturing Technology*, *30*(5-6), 425-433.
[26] Rajasekaran, R., & Iyengar, N.C.S.N. (2013). Peer-to-Peer JXTA Architecture for Continuing Mobile Medical Education Incorporated in Rural Public Health Centers. *Osong public health and research perspectives*, *4*(2), 99-106.https://doi.org/10.1016/j.phrp.2013.03.004
[27] Solimanpur, M., Vrat, P., & Shankar, R. (2004). Ant colony optimization algorithm to the inter-cell layout problem in cellular manufacturing. *European Journal of Operational Research, 157*, 592-606.
[28] Thiel, C.L., Needy, K.L., Ries, R., Hupp, D., & Bilec, M. M. (2014). Building design and performance: A comparative longitudinal assessment of a Children's hospital. *Building and Environment, 78*(130-136).
[29] Tongur, V., Hacibeyoglu, M., & Ulker, E. (2020). Solving a big-scaled hospital facility layout problem with meta-heuristics algorithms. *Engineering Science and Technology, an International Journal*, *23*(4), 951-959. https://doi.org/10.1016/j.jestch.2019.10.006
[30] Vos, L., Groothuis, S., &Van Merode, G.G. (2007). Evaluating hospital design from an operations management perspective. *Health Care Management Science*, *10*(4), 357-364. https://doi.org/10.1007/s10729-007-9034-7
[31] Rajkumar, R., & Sharma, V. (2019). Visualization of data mining techniques for the prediction of breast cancer with high accuracy rates. *Journal of Computational Science*, *15*(1), 118-130.
[32] Xu, Y.C., Dong, F.M., Liu, Y., Xiao, R.B., & Amos, M. (2010). Ant colony algorithm for the weighted item layout optimization problem. *arXiv preprint arXiv:1001.4099*.