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Response Time Improvement in Medical Emergency Departments Through Evolutionary Optimization

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Abstract. Modern Internet connectivity provides the ability to perform efficient communications between the control centre of a healthcare system and the internal management processes of the emergency departments in clinics. Based on this, resource management is improved when exploiting the available efficient connectivity for adapting to the operating state of the system. An efficient order of patient treatment tasks inside the emergency department can reduce in real-time the average treatment time per patient. The motivation to use adaptive methods and specifically evolutionary metaheuristics for this time-sensitive task, is the exploitation of the runtime conditions which may vary according to the patient incoming flow and the severity of each specific case. In this work, an evolutionary method improves the efficiency in the emergency department, according to the dynamically structured treatment task order. Specifically, the average time inside the ED is reduced at a small expense of the execution time. This renders similar methods as candidates for resource-allocating tasks.

Keywords. Swarm intelligence, Evolutionary methods, Emergency departments, Resource allocation, Ant Colony Optimization

1. Introduction

Emergency Departments (EDs) [1], [2] are an integral part of the services hospitals provide to patients, requiring urgent treatment. Incoming patient flows may vary according to dynamic conditions, but an ED must have the capacity to treat even the most severe cases. Inside there are different types of treatment beds, e.g., for simple cases, and at the same time, for severe. Incoming patients may undergo triage evaluation [3] which can assist in a scheduling decision from an algorithmic perspective. The next step is to provide a sequence of treatment tasks to each medical case. For the time period of a patient inside the ED, these tasks are offered according to the available resources, like doctor and nurse numbers. In case this treatment sequence is not efficient, e.g., time gaps exist in between tasks, the quality of offered services is reduced. A second scheduling

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decision relates to the mapping of each case's treatment sequence to the available resources. This is also a computational problem requiring an efficient solution.

Resource management inside the ED can be either static or dynamic [4], [5], [6]. The first category is characterised from simple resource-allocating procedures where the constantly changing runtime environment is ignored. Such methods require few computing resources to execute but provide inefficient results for the scheduling. On the other hand, dynamic allocation procedures exploit the runtime conditions and historical data for adapting to the operating environment and maximising that way the performance. Examples in this case include the detection of patterns inside the incoming flows [7] to use them for prediction of the future demand.

In the current research, swarm intelligence is chosen due to the ability to provide adaptivity to the dynamic ED nature which constantly changes according to the incoming patient flow and the state of the internal resources. It provides novelty due to the ability to curb the increasing complexity when the allocation problem to solve undergoes big increase in its computational space. For example, a big incoming patient flow and large amount of resources that need to be rearranged in realtime. Also, complex computational problems are solved heuristically. Due to these traits, the algorithm can be extended in the future to provide solutions to severe trauma cases when the medical systems must function in extreme conditions.

2. Medical Emergency Department Environment and ACOPath ED Algorithm

Inside the ED, the patient is allocated to a waiting queue in case all beds are occupied. When a bed becomes available, a waiting patient is chosen according to the weight of the case. An ED also contains resources like doctors and nurses. When the bed allocation is finished, an algorithm provides a sequence of treatment tasks for the patient. Every task is correlated to a resource. Between these tasks there may exist time gaps, so an efficient algorithm that adapts to the runtime conditions tries to minimise these gaps, leading to an efficient schedule. The sequence of the medical tasks is allocated utilising the ACOPath ED algorithm.

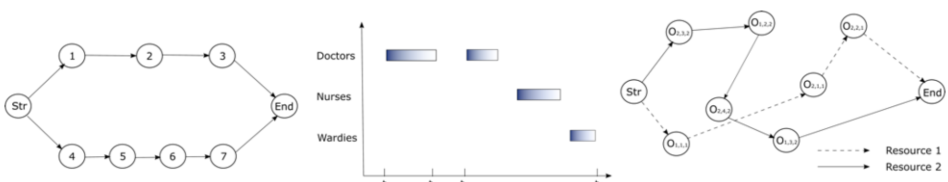

Figure 1. Left: Graph representation, Center: Task assignment, Right: Resource sequences.

In Figure 1-centre, a task sequence allocated to a specific patient is correlated to resource groups. Specifically, the first two tasks are allocated to doctors, the next one to a nurse and the last to the group of wardies. In Figure 1-right, the sequence of tasks for two specific resources is depicted. Specifically, each resource traverses a node sequence comprising tasks for specific patients. For example, the first resource starts with the first task allocated to the first patient. Next, it handles the first task of the second patient, and finally, the second task of the same patient. Notation $O_{j,i,r}$ denotes that patient j is at his task no. i with resource r.

Ant Colony Optimization (ACO) as a metaheuristic, emulates the behaviour of real ants while trying to find their food. They tend to deposit a chemical substance upon the traversal paths which evaporates along with time. The amount of this substance correlates to the possibility of subsequent ants following the same paths. This leads to higher concentration, pushing that way the procedure to a state of convergence. In a graph topology, a virtual ant traverses from a starting node to a specific end-node. The choice of the next neighbouring node is realised according to a function, considering the amount of pheromone upon the edge and other parameters related to specific problems for solving. Heuristics provide close-to-optimal solutions under complexity which yields feasible results. The algorithm forms a directional graph structure (Figure 1-left) depicting resource sequences. Next, all feasible connections between nodes are added, so ants are able to find paths (task sequences for specific resources) with optimised total cost. Then, these tasks within the paths are allocated to the resource corresponding to the starting node. When all resources are reallocated to tasks (no paths are left in the directional graph structure), the optimisation process is complete. In Figure 1-left, a directional graph structure is created for the purpose of facilitating the ACO algorithm execution. Each sequence from start to end, represents the patient tasks each resource has to traverse.

3. Results

There are five resource groups, i.e., doctors, nurses, wardies, pathology and x-ray labs. The simulation covers a four-hour time span in an ED with 5 beds, a relatively large queueing size of 100 for incoming patients, and a predefined set of treatment tasks offered to patients [8]. A triage priority for each patient is created by a uniform distribution between five levels. Patient interarrival times use a Poisson distribution.

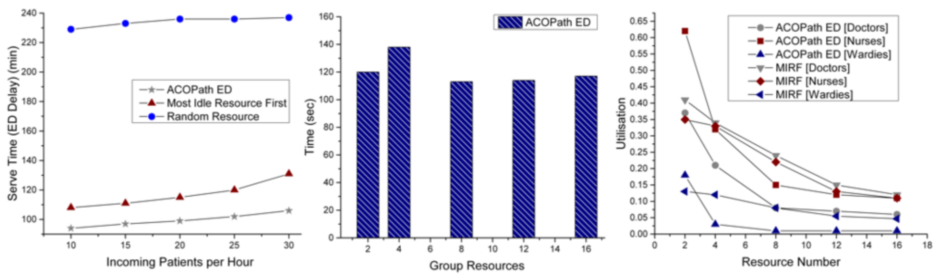

Figure 2. Left: ED delay, Center: Execution time, Right: Resource utilization.

In Figure 2-left, performing random resource allocation yields the highest delay time. In this case, each resource is picked up with a uniform distribution without considering the previous utilisation log. Next, if the most idle resource is prioritised, the average delay time is improved using the Most Idle Resource First (MIRF) algorithm. ACOPath ED returns the most efficient results since it adapts its functionality to the dynamic environment. In Figure 2-centre, ACOPath ED's execution time is depicted. The advantage of the algorithm is profound in EDs with high numbers of resources to allocate. When the search space of the problem to solve is low, e.g., 2 or 4 doctors in an ED environment with low patient incoming rate, typical brute force methods should outperform. In Figure 2-right, utilisation is depicted according to the increasing number of resources within each resource group. ACOPath ED is compared to the algorithm allocating the most idle resource first. Different resource groups undergo a utilisation percentage decrease since their number increases. More available resources within each group drop the average utilisation percentage. When the available resources are in low numbers, the utilisation percentage of ACOPath ED is higher since there is not enough space to perform its adaptivity.

4. Conclusion

Dynamically allocating resources in an ED, solves the main problem of the static pre-allocation which is unable to accommodate fluctuations in the incoming patient traffic load. Adaptive heuristics solve difficult computational problems in a feasible time frame. ACOPath ED adheres to these principles offering performance efficiency in the simulated ED environments. Typical allocating methods like those based on the prioritisation of the most idle resource, cannot offer advanced performance in dynamic environments.

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