A Scheduling Algorithm for the Optimal Acquisition of Biological Material in the Hospital Logistics

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Abstract

The biological material acquisition is a standard task of specimens' collection and transportation daily handled in hospitals, where coordination of the pick-up times is essential. The process is distributed in space since samples of biological material are taken randomly in time at several dispersed hospital departments but analyzed elsewhere in a special laboratory. We propose an algorithm for the acquisition of biological samples to achieve the highesttask throughput and compliance with delivery deadlines by minimal possible staff efforts spent. The main results are reflected in optimized acquisition unit's transportation paths and job schedules, as well as constructed wards' timetables. The major contribution concerns the integration of several approaches, from multi-criteria decision making and assignment problem to task sequencing based on the traveling salesperson problem solved with genetic algorithms. The implemented scheduling algorithm's results in a Slovenian hospital demonstrate immediate benefits regardingbetter-organized and themoreefficient working environment.

Keywords

Health service; Logistics; Optimization; Heuristics; Specimens' transportation in the hospitals; Job scheduling.

INTRODUCTION

The primary aim of healthcare institutions is to offer a high-quality medical service for treated patients. The hospitals are no exception here, where close cooperation between the different working units, such as hospital wards, is crucial to guarantee such a high-quality service. Since modern medical procedures can be quite complex, well-organized employment of medical work-flows is a fundamental prerequisite for any hospital to reduce corresponding costs and increase the level of services. On the other side, inefficient intra-facility logistics might significantly raise the costs of human resources and increase healthcare delivery, energy and other types of costs. This could, in turn, cause several serious problems, such as increased risks and other difficulties, which would consequently reduce the quality of patient care (Mavaji et al., 2014).

Transportation of different types of medical items (e.g., forms, records, medications, surgical material, and so on) often occurs in a medical workflow and can represent even more than 90 percent of all transportation activities in the hospitals (Mavaji et al., 2014). Furthermore, the other kinds of therapeutic items, such as medical samples and specimens (blood, urine, plasma, etc.), have to be also picked up at one position (hospital departments - wards) and delivered to another one (laboratory). Efficient coordination and scheduling of such so-called pick-up and delivery jobs are quite challenging research area that belongs to the field of specimens' collection and transportation in the hospitals (Fiegl and Pontow, 2009; Jorgensen et al., 2015; Wilson, 1996). Since the effective implementation of these kinds of jobs is not an easy task, the advanced use of information technology is required.

Moreover, even approximately 70% of clinicians' decisions are based on laboratory results, so their accuracy, quality, and precision are crucial in clinical care (Abdollahi et al., 2014). On the other side, it is estimated that nearly 70% of errors occur in the pre-analytical phase of sampling, taking into account the analysis request, collection, transportation, and preparation for analysis (Dunn, 2015; Jørgensen et al., 2013). Accordingly, while doing the transportation of samples, the time is crucial to guarantee the quality of the samples(Grasas et al., 2014).

The notable characteristics of the acquisition process can be described as follows (Becan McBride and Fried, 1985; Dunn, 2015; Salinas et al., 2010):

1. Samples are taken at many dispersed hospital departments and brought to a central site for analysis;
2. Biological samples are characterized using biochemical parameters that change with time. To properly analyze a sample, the time between uptake and the laboratory test (idle time) should not exceed the prescribed limit. Otherwise, the sample becomes useless and sampling has to be repeated;
3. The feasible idle time limits vary from one hour for blood samples up to 24 hours for other types of samples. The pace of the acquisition process is dictated by the lowest value of the idle time, meaning a system-wide maximum of 60 minutes of execution time.

As indicated above, the acquisition is carried out in one hour time intervals – referred to as acquisition cycles. In each cycle, two types of tasks have to be performed. The first one relates to the collection of biological samples at hospital wards, while the second one relates to transportation between hospital wards and the laboratory site. To satisfy the time limitations of the acquisition, both types of tasks are ascribed to 30 minutes of execution time.

Transfer of biological samples can be performed "manually" by medical staff or automatically by the use of different transport means, e.g. pneumatic tube systems(Jørgensen et al., 2013). In cases of pre-existing hospital infrastructure, the major disadvantage of incorporating such automatic transfer systems is high adaptation cost. Manual transport is a feasible option if proper information and tracking technology is in place. Hence, accurate information about the time and location of a biological sample shouldalways beavailable. Otherwise, the uncertainty related to the uptake times causes non-trivial organizational problems regarding the time management of the transport schedules and routes.

In this paper, we focus on a case study related to the manual acquisition of medical samples in the Celje hospital (CH), Slovenia. The existing acquisition process suffered from many serious deficiencies, such as bad coordination of various tasks, occurrence of erroneous samples, too excessive transportation distances and times, and so on. Thus, we were invited to make some enhancements to overcome their problems. We proposed a design of improved acquisition process, which would optimize assigning of wards to transportation path, their sequencing, and constructing of corresponding job schedules and ward timetables (see figure 1).To do so, we integrated several sophisticated approaches, from multi-criteria decision making and assignment problem solving to task sequencing based on the traveling salesperson problem (TSP) solved with genetic algorithms (GA).

The implemented results have demonstrated immediate benefits regarding the better-organized and more efficient working environment. The applied system enables the maximized number of successful pickups and deliveries while complying them with the time constraints. Moreover, a designed acquisition schedule also minimizes the overall transportation routes, maintains employees' satisfaction when performing transport services, as well as reduces the number of erroneous samples. Further, our framework is designed in such a way that provides the flexibility of the scheduling approach to accommodate each selected working environment.The paper is believed to contribute in the following ways:

1. There have not been practically any studies detected in the research field that would apply the whole plethora of different complex methodologies in a way as it was done in our study;
2. According to the information from the CH as a purchaser, the proposedscheduling mechanism runs successfully for more than four years already. It is not integrated into the hospital's information system yet, which means that it is "manually" recalibrated every six months based on results (hospital wards' timetables and acquisition unit job schedules) constructed in ourdevelopmentenvironment. The cost savings are significant, while the incidents with the corrupted biological material have practically totally disappeared.

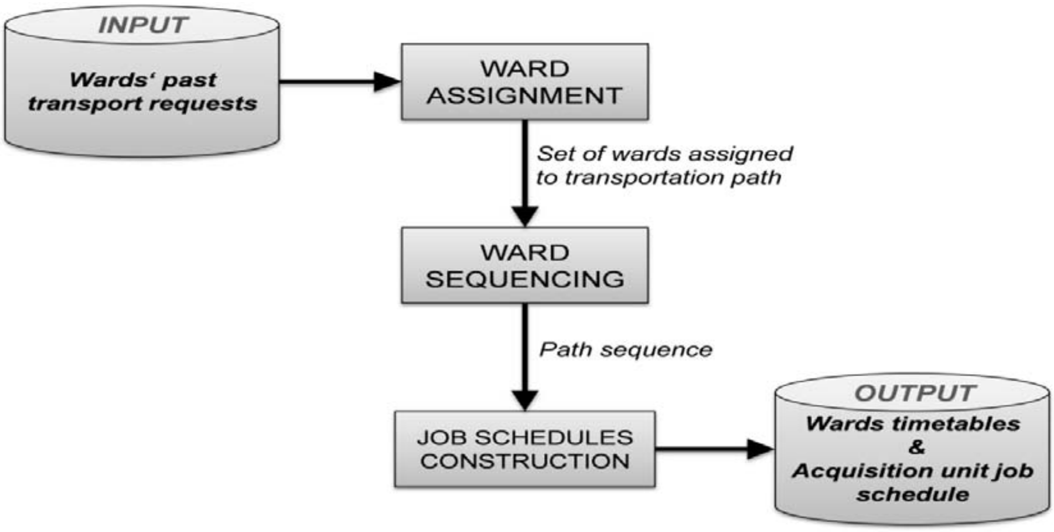


Figure 1: The conceptual design of improved acquisition process

Related Work

Our research is focused on so-called personnel scheduling, which consists of two-stage designing of job schedules or rosters for the execution of tasks (Ernst et al., 2004). The number of staff members is first determined, and then different tasks are assigned and performed. The problem of staff scheduling has been addressed in different transport systems, especially in public transport (Ernst et al., 2004). Applications can be found in call centers, hospitals, financial services, production and in other fields. A more detailed literature review of approaches in the field of nurse scheduling can be found in (Aickelin and White, 2004; Benazzouz et al., 2015; Bradley and Martin, 1991; Sitompul and Randhawa, 1990).

Careful investigation of the literature shows that there exists a significant lack of addressing a hospitals' transport scheduling under uncertain demands. Some studies may be found when considering external transport scheduling, as is the case of (Grasas et al., 2014). They aimed to improve the collection routes between hospitals, health centers, and two of the largest clinical laboratories in Spain while considering the vehicle's capacities and time windows between collection and delivery.

In the context of intra-hospital transport scheduling, particularly for the cases as ours, it turns out that only a few papers address a similar problem (e.g.(Jørgensen et al., 2013)). In (Jørgensen et al., 2013), the authors have tested the use of four different transportation modes: automated guided vehicles, pneumatic tube system, porters who are called upon as needed and porters who come to the wards every 45 minutes. Research reveals that the biggest potential in the sense of lowering the averaged idle time of samples is obtained by using a pneumatic tube system. However, these systems are less flexible regarding installation and route schedules. On the other hand, automated guided vehicles provide greater flexibility, but they require stricter monitoring and maintenance to achieve reliability and to detect a possible breakdown.

When considering a hospital or medical center with older infrastructure and a limited transport network, using porters seems to be the most appropriate and flexible way to perform the transportation process. However, the job construction under uncertain demand might be a quite difficult task since the acquisition unit does not have access to the real-time information about taken samples. A similar problem can be found in bus routing applications and timetables' setting (Mohaymany and Amiripour, 2009; Shangyao Yan et al., 2006; S. Yan and Tang, 2009). This type of applications is based on the coordination of interactions between the demand for transport services on the one hand and supply on the other hand. In most cases, coordination is achieved by taking into account historical records and by conducting a statistical analysis of the process (Zhang et al., 2011).

For difficult NP-hard problems, such as rostering, scheduling and resource allocation, standard constraint programming techniques alone might not be enough to find solutions efficiently. Since the real problems are complex and require efficient solving procedures, the use of heuristic and meta-heuristic approaches has become very popular (Banerjea-Brodeur et al., 1998; Fiegl and Pontow, 2009; Kramberger et al., 2009; Lapierre and Ruiz, 2007).Some other relevant literature from the field of health care planning management and hospital logistics can be found in works (Grand et al., 2019; Kadı et al., 2016; Patel and Patel, 2019; Vancroonenburg et al., 2016).

PROBLEM DEFINITION

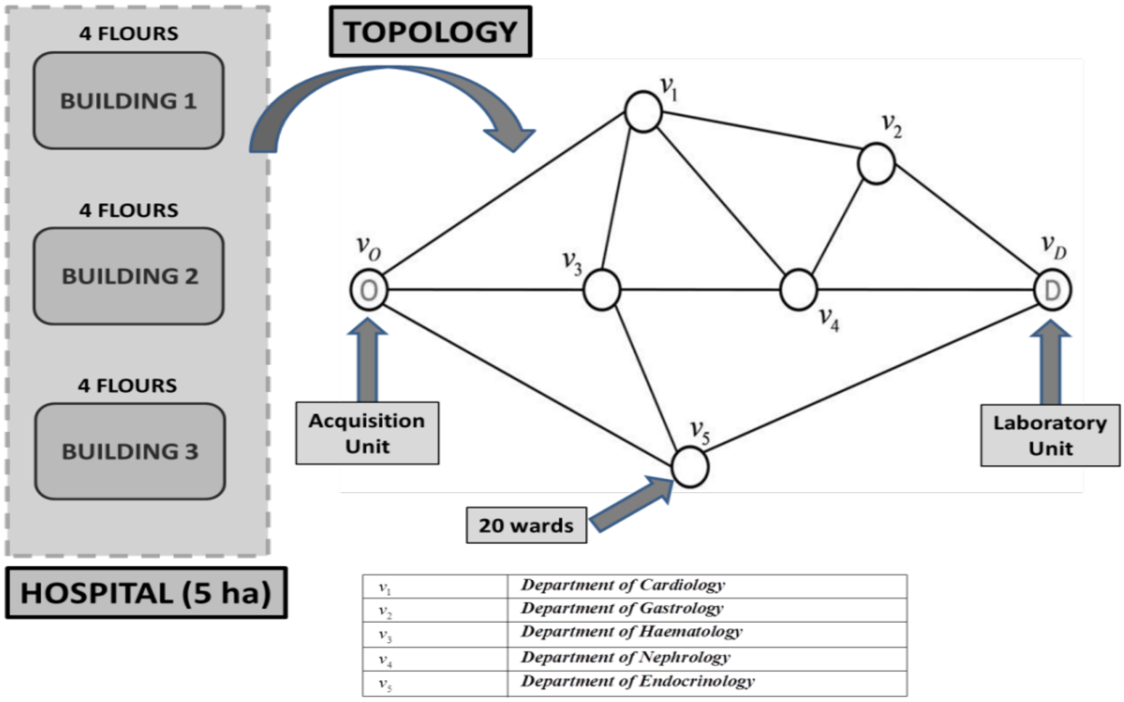
Topology of the hospital and detected problems

The Celje hospital has approximately 750 beds, and each year provides services for nearly 45000 patient admissions. It consists of 20 departments dispersed over three buildings spread across an area of 5 ha, each building having four floors (see figure 2). Three types of different hospital units are engaged in the acquisition of biological samples: the acquisition unit, 20 hospital wards, and the laboratory unit. After collecting of biological samples at hospital wards, two transport service staff members (porters) carry them to the laboratory, where they are analyzed.

In the past practice, the staff of the acquisition unit has been designing the transportation paths using only intuition and experience. Each transportation path was determined in advance and executed within one acquisition cycle, which takes about 1 hour. After careful analysis, it was discovered that within many acquisition cycles, the transportation paths had included vertices with no transport requests (unnecessary time consumption). On the other hand, the initial transportation paths often did not include vertices with high transport requests. Consequently, such vertices had to be treated individually as single-serviced, which rapidly increased a total distance traveled, as well as the time needed to complete the acquisition cycle.

Moreover, from the analysis of the past practice, it is detected that the information and communication facilities in the hospital are quite limited. Primary communication between the staff members is performed via telephones, whilethe acquisition unit (central communication node)is receiving calls from other units. As soon as a call from a ward is received, the transportation process has been started.

By analyzing this process, we noticed that coordination of assignment and scheduling tasks might have been quite laborious, especially in the case of several consecutive calls within a short period of time. Further, similarly as with transportation paths construction, such coordination has relied on the intuition and experience only. This practice has been recognized as inadequate since the overall transportation distances were too excessive, while the transportation times were too long.Even worse, since the total idle times have been too extensive, the samples often became corrupted, and the sampling had to be repeated again.



v_1	*Department of Cardiology*
v_2	*Department of Gastrology*
v_3	*Department of Haematology*
v_4	*Department of Nephrology*
v_5	*Department of Endocrinology*

Figure 2: The topology of the addressed hospital with symbolic representation of wards as graph vertices

Problem formulation in the sense ofgraph theory

The acquisition schedule depends significantly on the spatial distribution of the hospital wards. This topology can be represented as an undirected graph with a set of vertices v_i and connections among them (see figure 2). Each vertex has a different location in the hospital, whilethe connections represent the shortest routes for traveling between two adjacent vertices.

The acquisition process begins at the acquisition unit, which is the vertex labeled "O" (origin), and ends in the laboratory, which is the vertex labeled "D" (destination). According to [20], the transportation path can be represented by a sequence of vertices and vectors, where some of the vertices or vectors can be repeated. The transportation path is open because the first and the last vertex are different.

We distinguish between two major types of vertices regarding the transportation path:

1. The vertices in which there are samples ready to be transported to the laboratory (vertices with a transport request (TR)).
2. The vertices in which there are no samples ready to be transported (empty vertices (EV)).Considering the latter, sometimes it might happen that some vertices, although being part of the transportation path, have no samples ready for transport.

The whole idea of such acquisition path planning is to select a path with the maximal number of vertices of type TR and a minimal number of vertices of type EV. At the end of an acquisition cycle, a vertex is associated with one of the four possible attributes: successful vertex (type TR), failed vertex (type EV), single-serviced vertex (type SS), and residual vertex(type RV) (see figure 3).

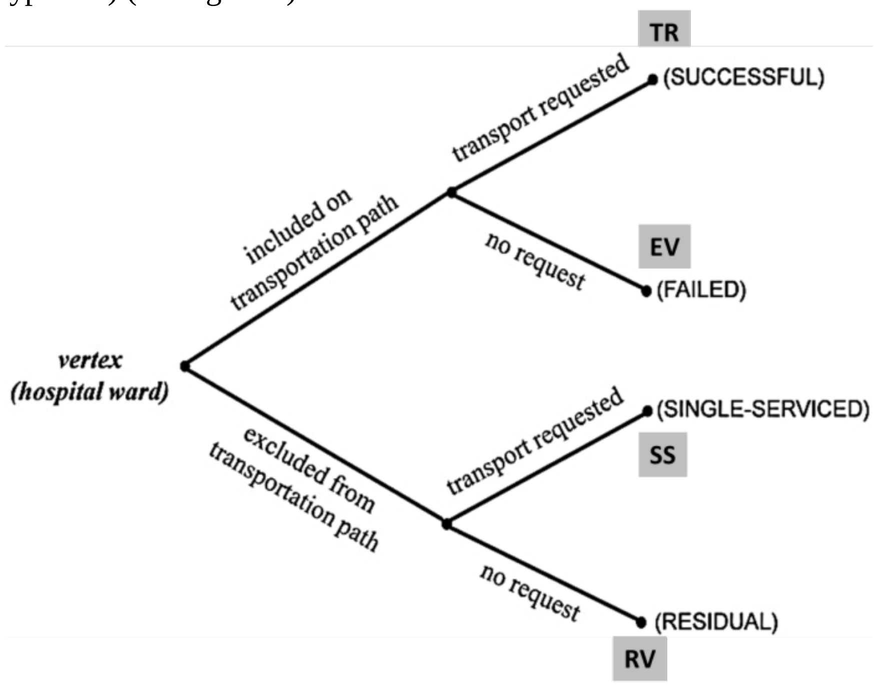


Figure 3: Four possible attributes associated with a vertex in an acquisition cycle

A vertex is successful if after made a transport request, it is included in the transportation path. Conversely, a vertex is said to be failed if no transport request is made and it is included in the transportation path. A vertex is denoted single-serviced if it is not incorporated in the transportation path but it made a transport request. Each single-serviced request is treated individually on account of the received telephone calls to the acquisition unit. The attribute residual corresponds to a vertex that is not associated with the transportation path, and it did not make a transport request.In the sequel, we will illustrate the applied notions with an example (see figure 4).

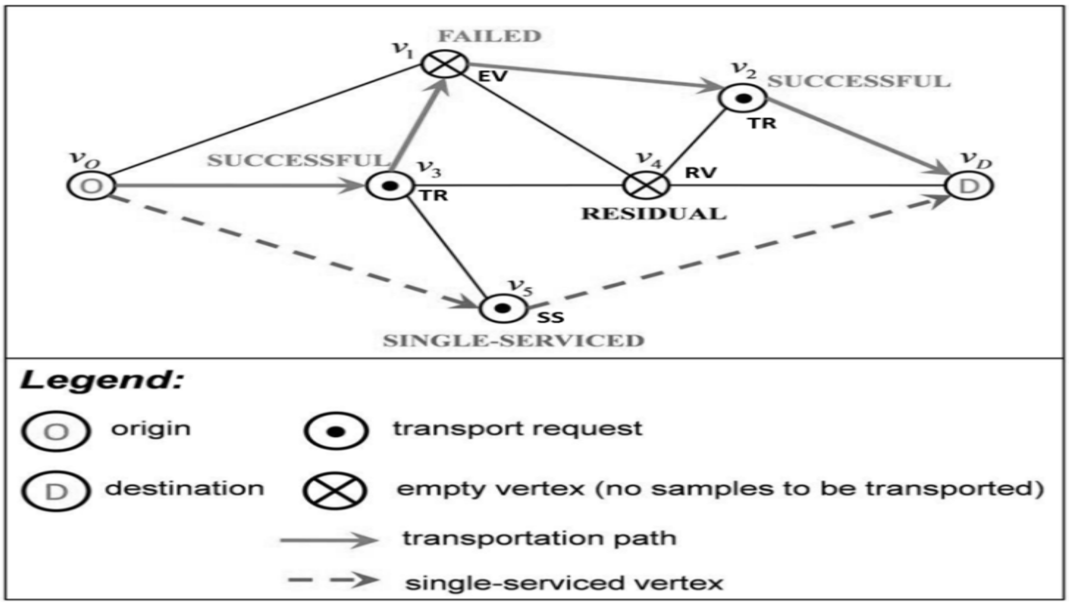


Figure 4: An example of acquisition of biological material

In figure 4, let us assume an acquisition cycle with the transportation path starting at the acquisition unit v_O and continuing at hospital wards v_3, v_1 and v_2 where samples are taken and then delivered to the laboratory unit v_D. In the case of "successful" wards v_3 and v_2, samples are picked up, while the "failed" ward v_1 sent no request for transport services. Ward v_5 is treated as single-serviced since it is not included in the transportation path, but it has a transport request. The ward v_4 is treated as residual since it does not belong to the transportation path and has no transport request.

CONCEPTUAL FRAMEWORK AND RESEARCH DESIGN

Concept, hypotheses, and main goals of research

The hospital management would like to increase the efficiency level of the acquisition process by employing some strategic decisions about the workflow of hospital units. The latter particularly regards atimely deliveryof all biological samples to the laboratory unit to avoid a repetition of the acquisition process and additional related costs.

The nature of this optimization problem is not trivial since different restrictions must be considered, such as time limitations, limited sources for acquisition, interdependencies between acquisition unit and hospital wards, etc. Here, several mutually-excluding criteria have to be addressed, and adequate trade-offs have to be found.

Nevertheless, the overall goal criterion of our approach tends to avoid unnecessary paths and increase the number of successful vertices, which can be achieved by avoiding single-serviced and failed vertices. The first type of vertices possessa high transport request frequency,so we should not treat them as individual tasks. Conversely, the second type of vertices does not possessthe high transport request frequency and should be therefore excluded from the planned transportation paths.

In our approach, we would like to coordinate the work between the hospital units efficiently by introducing three essential issues:

1. *Construction of the adequate transportation paths;*
2. *Providing information about the location and the approximate uptake time;*
3. *Providing information about the approximate delivery time.*

This kind of approach relies on the wards' past transport requests and consists of three successive steps (see figure 1):

1. **Ward assignment:** wards are associated with the transportation paths based on their transport request**.**
2. **Ward sequencing:** we determine the sequence by which wards associated with the transportation path are visited.
3. **Job schedules construction**: the most suitable job schedule is derived and, accordingly, the ward timetables are constructed. They define times at which a porter should arrive at a particular ward.

Conceptual framework of the optimization algorithm

Based on figure 1, we can roughly introduce the entire working mechanism of applied optimization algorithm as illustrated in figure 5. More precise details about applied variables and algorithms that appear in this framework (i.e., Algorithms 1 and 2, etc.) will be explained later in the following sections. The main core of the entire algorithm is engaged within the scope of three major parts: assigning of wards to transportation path, their sequencing, and constructing of corresponding job schedules and ward timetables.

As can be seen in figure 5, the whole optimization strategy of imitated (emulated) events is based on historical data for given past acquisition cycles related to individual wards. On this grounds, we can derive such quantities as a number of successful, failed, single-serviced (SS) and residual vertices, the number of transport requests (TR) or no requests, and the probability of TR. Then, we apply a probability related threshold parameter *p*, which is changing in a given interval. It essentially influences on a number of included wards in the current transportation path while doing the ward assignmentfor each acquisition cycle (***Algorithm 1***).

Further, we can compute a total number of failed and single-serviced vertices for all cycles at a given value of *p*, whereas the Dijkstra algorithm is conducted to calculate distances related to SS vertices of corresponding wards. Afterward, in a phase of sequencing (***Algorithm 2***), we obtain an optimally sorted sequence of included wards for each acquisition cycle by means of solving TSP with genetic algorithms. If the first porter's emulated traveling time exceeds 30 min, the second porter is also engaged in executingthe current transportation pathof each acquisition cycle. Further in algorithm 2, total walking distances related to SS wards, as well as total length of "empty" paths (empty path's fractions for failed vertices) arealso computed.

In the final step, labor costs spent for SS and failed vertices are derived for a given parameter *p*, whichis afterward increasedin the next iteration step. The described iterative process is in the sequel repeated for all remaining values of *p*, which gives us an objective function $J(p)$ as the main result. At last, we can find an optimal *p** = *argmin J*, which returns the most adequate job schedules for the acquisition unit.

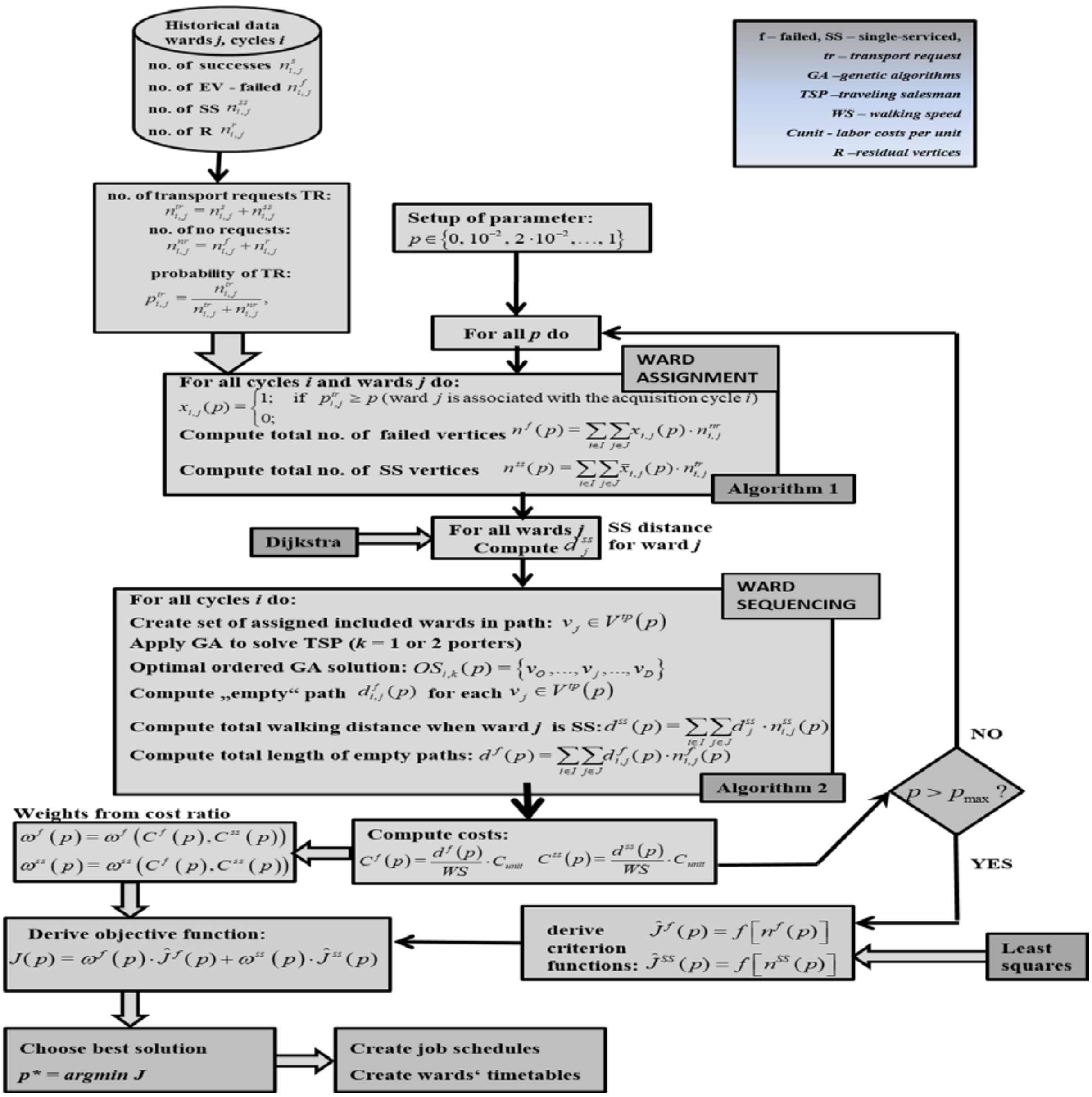


Figure 5: The entire working mechanism of the applied optimization algorithm

Ward assignment

Ward assignment is the first major task of the optimization algorithm shown in figure 5. Its precise mechanism can be seen in a pseudo-code *“**Algorithm 1”*** below in this section. It is based on the expectation of a ward's transport request. The probability that a request will be sent from a wardis derived from collected data on the basis of past observations. Biological samples are collected between 6 a.m. and 4 p.m. at 20 different wards. This periodis discretized into incremental periods of 1 hour, which represent 10 acquisition cycles. The planning horizon was set to 1 week.

Let us now associate notations related to the ward $j \in J$ in an acquisition cycle $i \in I$, where $J := \{1,\ldots,20\}$ and $I := \{1,\ldots,10\}$. The number of vertices labeled "successful" is given by $n_{i,j}^{s}$, while the number of vertices labeled "failed" is given by $n_{i,j}^{f}$. On the other hand, the number of single-serviced vertices is presented by $n_{i,j}^{ss}$, while the number of vertices labeled "residual" is defined by $n_{i,j}^{r}$. The number of vertices with a transport request $n_{i,j}^{tr}$ and those with no transport requests $n_{i,j}^{nr}$ at ward j and acquisition cycle i can be presented as the following two sums:

$$n_{i,j}^{tr} = n_{i,j}^{s} + n_{i,j}^{ss}, \qquad n_{i,j}^{nr} = n_{i,j}^{f} + n_{i,j}^{r} \tag{1}$$

Now we can derive the probabilities of transport request (*tr*) or no request (*nr*) for each vertex j in an acquisition cycle i:

$$p_{i,j}^{tr} = \frac{n_{i,j}^{tr}}{n_{i,j}^{tr} + n_{i,j}^{nr}}, \qquad p_{i,j}^{nr} = \frac{n_{i,j}^{nr}}{n_{i,j}^{tr} + n_{i,j}^{nr}} \tag{2}$$

where $p_{i,j}^{tr} + p_{i,j}^{nr} = 1$. As we could already see in figure 5, the corresponding ward is associated with the transportation path only in the case when $p_{i,j}^{tr} \geq p \in [0,1]$. Thus,the ward assignment to the transportation path canbe expressed with the following dummy variable:

$$x_{i,j}(p) = \begin{cases} 1; & \text{if} \quad p_{i,j}^{tr} \geq p \text{ (ward } j \text{ is associated with the acquisition cycle } i\text{)} \\ 0; & \end{cases} \tag{3}$$

Now let us observe the whole ward assignment mechanism presented in ***Algorithm 1*** below. Here, inputs are variables $n_{i,j}^{tr}$, $n_{i,j}^{nr}$ and threshold probability p. When both loops (for cycles *i* and wards *j*) are completed, the dummy variable is accordingly loaded with ones or zeros, so the transportation paths are determined for all acquisition cycles. Afterward, the algorithm calculates the variables $n^{f}(p)$ and $n^{ss}(p)$. The first one represents a total number of vertices labeled "failed" for all acquisition cycles and given value p. It is derived from the dummy variables and the number of vertices with no requests ($n_{i,j}^{nr}$) in the following way:

$$n^{f}(p) = \sum_{i \in I} \sum_{j \in J} x_{i,j}(p) \cdot n_{i,j}^{nr} \tag{4}$$

Similarly, the total number of single-serviced vertices $n^{ss}(p)$ is calculated as follows:

$$n^{ss}(p) = \sum_{i \in I} \sum_{j \in J} \bar{x}_{i,j}(p) \cdot n_{i,j}^{tr} \tag{5}$$

where $\bar{x}_{i,j}$ is complementary to the $x_{i,j}$. When the ward assignment is completed, we obtain the set of vertices that belong to the transportation paths. In the following section, the order of visited vertices on the path is going to be also determined.

Algorithm 1 Ward assignment(pseudo-code)

input: $n_{i,j}^{tr}$, $n_{i,j}^{nr}$, p

for all acquisition cycles
for all wards
compute $p_{i,j}^{tr}$ // (from (2))
if $p_{i,j}^{tr} \geq p$ // (see (3))
$x_{i,j}(p) = 1$
else
$x_{i,j}(p) = 0$
end (**if**)
end(**for**)
end(**for**)
compute $n^{f}(p) = \sum_{i \in I} \sum_{j \in J} x_{i,j}(p) \cdot n_{i,j}^{nr}$ // (from (4))

compute $n^{ss}(p) = \sum_{i \in I} \sum_{j \in J} \bar{x}_{i,j}(p) \cdot n_{i,j}^{tr}$ // (from (5))

output: $x_{i,j}(p)$, $n^{f}(p)$, $n^{ss}(p)$

Ward sequencing

Determining a suitable succession of pick-ups and deliveries belongs to the class of the traveling salesperson problem. In the TSP, each vertex must be visited precisely once regarding the shortest total route as an optimization criterion [(Larrañaga et al., 1999; Wei and Yuanzong, 2010). In the hospital, each transportation path starts at the acquisition unit, then continues across the associated wards, where biological samples are collected, and finishes once the samples are delivered to the laboratory. Therefore, we are dealing with constructing transportation paths containing different origins and destination vertices. Procedures for solving TSP problems are usually appliedin transport network modeling. As we have seen in previous sections, the transport model is based on a hospital topology in our case.

Before starting the ward sequencing algorithm from figure 5 (***Algorithm 2***), a calculation of shortest distances between network's vertices is previously needed, for which we have chosen the Dijkstra's algorithm (Kramberger et al., 2009). Based on calculated network distances, one can also calculate the path length traversed by a staff member when the ward j is single-serviced. For a single-serviced vertex, we assume that the staff member begins the route at the acquisition unit, continues to the selected ward j and finishes the route in the laboratory unit. For each ward, this distance is denoted by d_j^{ss}.

The precise mechanism for ward sequencing, a second major task of the optimization procedure from figure 5,can be seen in a pseudo-code"***Algorithm 2"*** below in this section. Here, the initial set $V = \{v_O, v_1, ..., v_{20}, v_D\}$ representing all vertices is first applied.Afterward, for each acquisition cycle, variable $x_{i,j}(p)$ ensures that wards v_j included in the current transportation path are added to the set of assigned wards $V^{tp}(p)$. At this point, the latter does not include the sequence of visited vertices on the transportation path yet.

In the next step, the genetic algorithms are applied to solve the corresponding TSP problem. We used GA with permutation encoding and with a combination of the following mutation operators: exchange mutation operator, simple inversion mutation operator, and scramble mutation operator (Larrañaga et al., 1999). Similar to (Wei and Yuanzong, 2010), the initial population is spread randomly within the search space, such that the global minimum can be found. The genetic algorithm used in task sequencing was adopted from (Kirk, 2014). The algorithm includes a framework for solving a multiple TSP problem. Therefore, we can apply it to a case of constructing single or multiple transportation paths, where more than one porter can be used in a given acquisition cycle.

When an optimal solution to the TSP using GA is generated, the order of visited vertices for the acquisition cycle i and the first staff member $k = 1$ is as follows:

$$OS_{i,k}(p) = \{v_O, ..., v_{prev}, v_j, v_{next}, ..., v_D\} \tag{6}$$

In the optimal solution, v_j represents a visited ward j, v_{prev} is prior visited ward and v_{next} is the following visited ward in the given order. For an obtained path sequence and given staff member $k = 1$, we can derive the total length of the transportation path d_i^{tp}. Based on the total length and estimated traveling speed, the total time t_i^{tp} for executing constructed transportation path can also becalculated. The latter includes the waiting time at wards as well, which involves an examination and preparation of biological samples by personnel.

Travel time on a transportation path must be carried out within 30 minutes. If the total time t_i^{tp} in the obtained solution exceeds 30 minutes, then expression (6) is calculated for two staff members from the acquisition unit $k \in K$, $K := \{1,2\}$. Accordingly, two different transportation paths for a given acquisition cycle i are derived.

In the following step, for a given acquisition cycle i and suggested transportation paths, we calculate the "empty" fraction of the traveled path for each associated ward $v_j \in V^{tp}(p)$. Such*empty path*corresponds to a distance walked when a failed vertex is serviced. It can be calculatedas a difference between the fixed path length and the length of the path in the case when the corresponding ward j is not visited. Thus, the empty path length for ward j and acquisition cycle i can be calculated by the following expression:

$$d_{i,j}^{f}(p) = d_{v_{prev},v_j} + d_{v_j,v_{next}} - d_{v_{prev},v_{next}} \tag{7}$$

When a loop for acquisition cycles in ***Algorithm 2*** is completed, we can computethe total distance $d^{ss}(p)$ walked by staff when the ward j is single-serviced. This distance is calculated as a sum of the distance walked for each single-serviced ward d_j^{ss} and the number of vertices being single-serviced $n_{i,j}^{ss}(p)$ at given p:

$$d^{ss}(p) = \sum_{i \in I} \sum_{j \in J} d_j^{ss} \cdot n_{i,j}^{ss}(p) \tag{8}$$

Another output derived from the sequencing procedure represents the total length of empty paths $d^{f}(p)$. The latter is derived from the sum of each ward's empty path length $d_{i,j}^{f}(p)$ and the number of vertices with no transport request $n_{i,j}^{f}(p)$ at given p:

$$d^{f}(p)=\sum_{i\in I}\sum_{j\in J}d_{i,j}^{f}(p)\cdot n_{i,j}^{f}(p) \tag{9}$$

From a description of A***lgorithm 2*** becomes evident that the main goal of task sequencing is toderive the traveled distance and time spent on executing empty paths and single-serviced vertices.

Algorithm 2 Ward sequencing (pseudo-code)

input: $x_{i,j}(p)$, V , p , d_j^{ss}

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for all acquisition cycles
$V^{tp}(p)=\{\ \}$
for all wards
if $x_{i,j}(p)=1$
$v_j \in V^{tp}(p)$
else
$v_j \notin V^{tp}(p)$
end (**if**)
end (**for**)
apply GA to solve TSP (one porter)
compute $d_i^{tp}(p)$ and $t_i^{tp}(p)$
if $t_i^{tp}(p)>30min$
apply GA to solve multiple TSP (two porters)
end (**if**)
compute $d_{i,j}^{f}(p)$ with respect to GA solution for each associated ward $v_j \in V^{tp}(p)$:
$d_{i,j}^{f}(p)=d_{v_{prev},v_j}+d_{v_j,v_{next}}-d_{v_{prev},v_{next}}$ // from (7)
end (**for**)
compute $d^{ss}(p)=\sum_{i\in I}\sum_{j\in J}d_j^{ss}\cdot n_{i,j}^{ss}(p)$ // from (8)
compute $d^{f}(p)=\sum_{i\in I}\sum_{j\in J}d_{i,j}^{f}(p)\cdot n_{i,j}^{f}(p)$ // from (9)

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output: $d^{ss}(p)$, $d^{f}(p)$, $OS_{i,k}(p)$

Finding an optimal solution forthe entire optimization problem

The precise mechanism of finding an optimal solution of the given optimization problem can be seen in a pseudo-code "***Algorithm 3"*** below in this section. It actually comprises all main stages of entire optimization algorithm in figure 5. Accordingly, the issues discussed here rely on previously presented algorithms in this paper. As it could be already seen in figure 5, the whole optimization procedure is executed on the grid $p\in\{0,10^{-2},2\cdot10^{-2},\ldots,1\}$, where a threshold parameter$p$ controls the central loop of the entire optimization algorithm (see figure 5). By changing it withinan interval [0,1], we obtain 101 different acquisition schedule alternatives based on given past observations. Our goal is to select the most adequate alternative with respect to the following derived multi-criteria objective function (see figure 5):

$$J(p) = \omega^f \cdot \hat{J}^f(p) + \omega^{ss} \cdot \hat{J}^{ss}(p) \tag{10}$$

Here, the first criterion $\hat{J}^f(p) = f\left[n^f(p)\right] = \hat{n}^f(p)$ represents an analytical regression function fitting the total number of the failed vertices $n^f(p)$ (expression (4)) with respect to *p*. Similarly, the second criterion $\hat{J}^{ss}(p) = f\left[n^{ss}(p)\right] = \hat{n}^{ss}(p)$ is a regression function fitting the $n^{ss}(p)$ (expression (5)) with respect to *p*. Both functions are estimated by means of least squares(LS) regression and are derived as shown in figure 6.

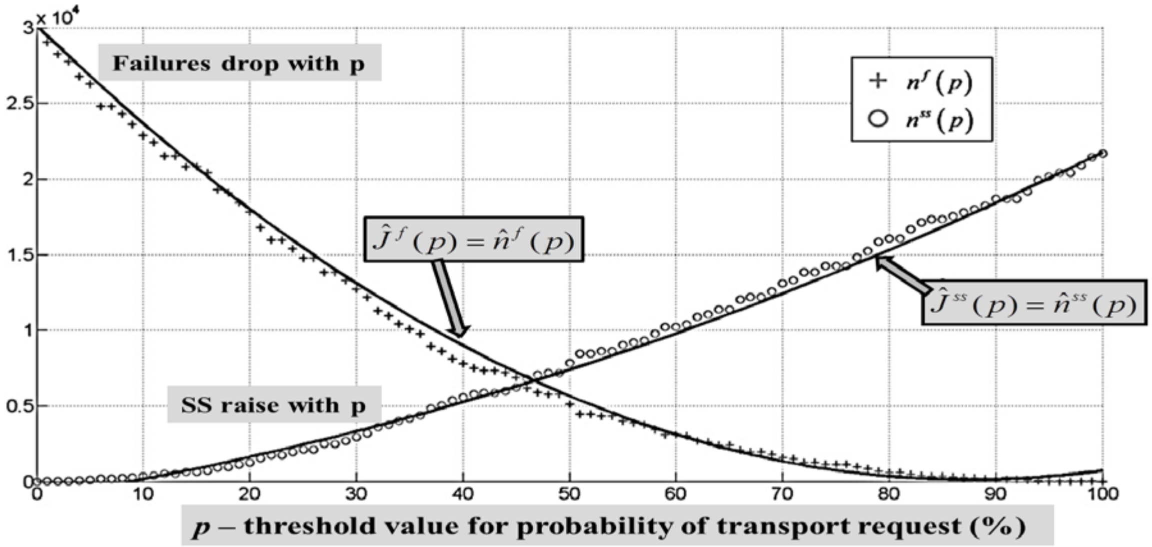

Figure 6: Analytical regression functions $\hat{J}^f(p) = f\left[n^f(p)\right]$ and $\hat{J}^{ss}(p) = f\left[n^{ss}(p)\right]$

By observing regression functions from figure 6, we can see that we are dealing with the multi-criteria optimization problem. Since the values of decision criteria do not have equal importance, we have to determine weights ω^f, ω^{ss} for each criterion. This task can be done by first calculating labor costs related to failed and single-serviced vertices and then calculating a ratio between each criterion based on the costs. For a given *p*, the labor costs related to the failed and single-serviced vertices can be calculated using the following expressions:

$$C^f(p) = \frac{d^f(p)}{WS} \cdot C_{unit}, \qquad C^{ss}(p) = \frac{d^{ss}(p)}{WS} \cdot C_{unit} \tag{11}$$

where $d^{ss}(p)$ and $d^f(p)$ have been introduced in the expressions (8) and (9), respectively, WS is the average walking speed of the workforce, and C_{unit} are the labor costs per unit.

Once labor costs for each alternative are calculated, we can obtain the total failed and single-serviced labor costs C^f and C^{ss}, considering all alternatives. Based on the ratio between C^f and C^{ss} we can afterward calculate the weights ω^f and ω^{ss} of the function (10) as well. This way, by having determined all quantities in function $J(p)$, it can be obtained for all values of parameter *p*. In the last step of ***Algorithm 3***, we can derive afinal solution to our optimization problem, which sits at the extremum of the function $J(p)$ in (10).

Algorithm 3 Finding optimal solution of optimization problem(pseudo-code)

input: $n_{i,j}^{tr}$, $n_{i,j}^{nr}$, V , d_j^{ss}

$p = 0$
while $(p \leq 1)$
execute algorithm ***Ward assignment (Algorithm 1)***
execute algorithm ***Ward sequencing (Algorithm 2)***
compute costs $C^f(p)$ and $C^{ss}(p)$ // from (11)
$p = p + 0.01$
end (**while** p)
determine weights ω^f and ω^{ss} // from the ratio between C^f and C^{ss}
derive analytical regression criterion functions $\hat{J}^f(p)$ and $\hat{J}^{ss}(p)$ with LS // see figure 6
calculatethe objective function: $J(p) = \omega^f \cdot \hat{J}^f(p) + \omega^{ss} \cdot \hat{J}^{ss}(p)$
determine $p^* = \operatorname{argmin} J$

output: p^*, theoptimal solution needed to create Job schedules

Background behind constructedjob schedules and wards' timetables

As it could be seen in the previous section, finding the most appropriate value of the parameter p^* in fact also means achieving the trade-off between the minimal number of failed vertices and the minimal number of single-serviced vertices.Namely, figure 6 has shown us that historical data have such nature,which dictates a dropping of a number of failed vertices while increasing the threshold probability of transport request p. Conversely, a number of single-serviced services is rising while increasing the value of p.

The obtained argument p^* enables us to construct the most adequate job schedules for the acquisition unit. Job schedules for each staff member consist of the followingmajor attributes (see an example in figure 7, part a) – "*Job schedule 1*"):
1. The sequence of which the wards associated with the transportation path are visited.
2. An arrival time of the staff member at each associated ward.
3. Atotal timeof execution of the corresponding transportation path.

To meet the time limits imposed by the acquisition process, the coordination between the collection of biological samples at hospital wards and transportation services has to be maximally synchronized. The wards are familiar with an execution time of pickup and delivery tasks by using ward timetables that are constructed based on given job schedules. Ward timetables consist of the observed acquisition cycle, type of the supply, and arrival times (see part b) in figure 7). The arrival times enable wards to organize their own working processes so that samples are timely prepared for acquisition. The first time represents the arrival time when a member of the acquisition unit visits the selected ward, while the second time represents the arrival time to the laboratory. On account of the one-hour time limit in sample idling time, the biological samples are expected to be delivered to the laboratory on time.

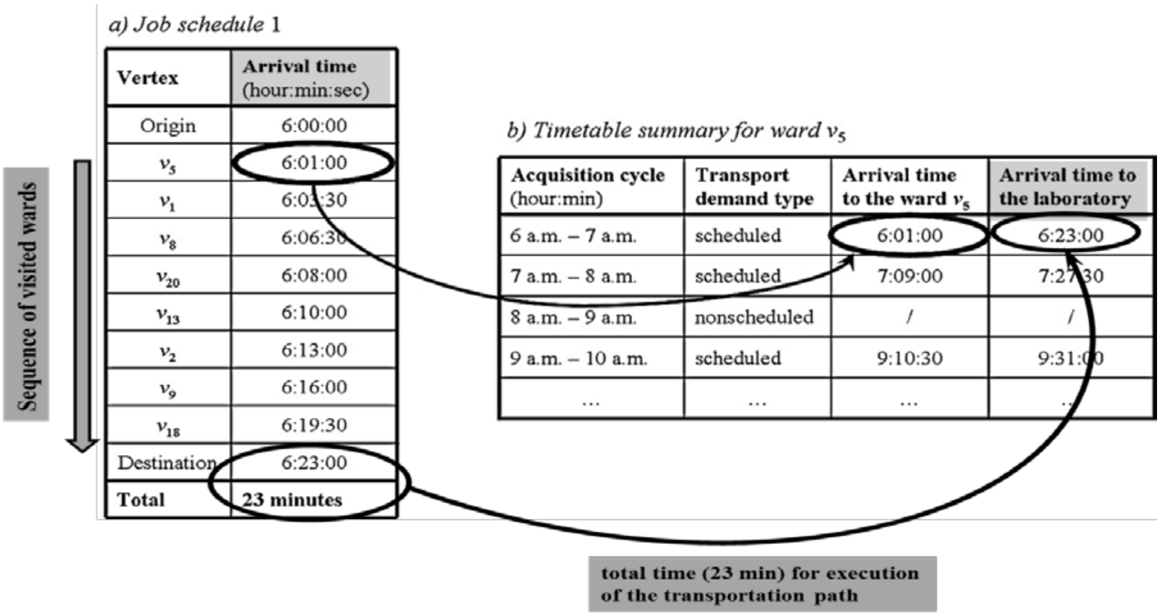

Figure 7: An example of constructing the Work timetable from the Job Schedule

Practical Numerical Results

Comparison with Initial Performance

The proposed algorithm was developed in the MATLAB environment. The calculation of results was performed on an Intel i7 2.93GHz processor with 8GB RAM in the Microsoft Windows 7 environment. The computation of all 101 alternatives for the acquisition process lasted 6.09 minutes, from which more than 99.9% of that time was spent solving the applied TSP.

The computational results of our algorithm were compared with the initial performance, where job schedules were constructed by relying only on intuition and experience (see Table 1). While searching an appropriate balance between the minimal number of failed vertices and those of single-serviced vertices, we have taken into account that the total costs related to SS vertices are **three times** higher. On these grounds, we have managed to settle the weights ω^f and ω^{ss} of the objective function (10) appropriately.As it turned out, the most adequate solution to our optimization problem was found when parameter p has taken the value: $p^* = 0.25$.

The obtained results from Table 1 show that approximately 10% more vertices are included in the transportation paths, although a total length of the transportation paths is shortened roughly by 20%. On the selected paths, there are also 20% more successful vertices while single-serviced vertices are reducedby less than one percent of the total.However, we should emphasize that the total distance walked for single-serviced vertices is reduced even by 62%; consequently, the walking distance for those vertices represents nearly two-thirds of improvement if compared withthe initial performance.

Comparison (daily basis) **for:**	**Initial performance**	**Proposed algorithm**

		(p^* = 0.25)
n^s (success)	62	**75**
n^f (failure)	58	**56**
n^{ss} (single service)	21	**8**
Total distance walked for single-serviced vertices (*m*)	6 515.7	**2 516.46**
Total length of transportation paths (*m*)	23 105.3	**18 494.6**

Table 1: Results of comparison of our solution with the initial performance

The solution of proposed algorithm and corresponding transportation paths can be used for constructing of the most suitable porters’ job schedules, as well as for creating of adequate wards’ timetables. Transportation paths that are integrated intothe job schedules will remain fixed as long as the hospital wards' pickup requests do not start to vary excessively. Regarding this issue, an analysis of historical data showed that the pickup requests have on average quite steady nature. Moreover, historical analysis has also shown that the volumes of wards’ collected samples do not fluctuate significantly as well. From all this it is expected that future variations of requests will remain to be on the low level. Otherwise, the transportation paths, job schedules, and ward timetables will be needed to be reconstructed. However, as it was already emphasized in the introduction section, the applied system turns out to be quite effective from the starting time of its implementation several years ago. Moreover, the historical analyses during this time period confirmed that there have been no significant variations of the pickup requests and collected samples’ volumes.

Discussion about implementation issues

Currently, the hospital's information system does not support the integration of the proposed scheduling framework yet. Therefore, algorithms' outputs, i.e. hospital wards' timetables and acquisition unit job schedules, are remaining to be constructed in the MATLAB environment. Despite this, the latter are provided beforehand to the hospital units, so they have an opportunity to test them in their everyday work operations.Moreover, since the transportation paths are fixed over a certain period of time, the staff members always have a chance to get accustomized to possible changes in the job schedules or wards' timetables.

The process of implementing our solution into the hospital's environment lasted approximately three months. In the beginning, it was carefully observed with the intention of testing adequacy of coordination of working activities on the bases of calculated times of job schedules’ and ward timetables’. After three months of observation, we found that the calculated results are achieved in practice as well, and the employees have entirely accepted the complete overhaul. They believe that the adopted changes ease their work, especially from the achieved coordination and better organization of work activities.

From today's point of view, more than four years have already passed since our algorithm's outputs were implemented into the hospital's everyday practice. Having observed no major changes in hospital wards' requests, the initially proposed schedules are more or less still in use. With the acquisition unit, we have agreed to verify the statistics every six months or more frequently if necessary. In a case of more intensive requests’ variations, the transportation paths, job schedules, and ward timetables will be re-calibrated.

Despite the fact that our scheduling framework has not been implemented into the information system yet, and the transportation paths are being fixed over a longer period of time, the acquisition unit'smembers are able to deal with unscheduled intra-day requests more efficiently. For a given acquisition cycle, one or at most two transportation paths are needed. Since they last no more than 30 min, both porters have at least half an hour of additional time for dealing with telephone requests or helping other members of the acquisition unit.

Further discussion about achieved results

Our solution has an empirical, as well as a methodological background, where significant efforts were dedicated to the design of transportation paths that do not rely on intuition and experience. Moreover, we were able to identify which hospital wards register high or low transport requests with respect to different time periods of the day. On these grounds, we managed to find a trade-off between the number of successfully visited vertices on one hand, and a number of failed and single-serviced vertices on the other. Not only were we able to maximize the number of pick-ups and deliveries, but we managed to minimize overall transportation paths as well.

Moreover, the achieved synchronized coordination of transport services and wards' activities also provides the highest possible task throughput. Since the path distance and time spent are correlated, the decrease in total traveling distance influences the reduction of lead time as well. Furthermore, the proposed algorithm not only decreases the time devoted to working operations but also results in a more organized working environment.

CONCLUSION

In the paper, an algorithm for the acquisition of biological material is presented. The latter consists of two different types of tasks and three types of working units. At hospital wards, biological samples are taken from the patients while the transportation of samples between wards and the laboratory site is performed by members of the acquisition unit. The proposed algorithm is shown to achieve the highest task throughput due to the achieved coordination of working units, consequently yielding a better working environment. Moreover, the obtained results comply with the delivery deadlines and also minimize staff effort in terms of time consumption from the distances being traveled.

The scheduling algorithm integrates several mathematical approaches and consists of three successive steps. Due to the historical observations from hospital practice, the wards are firstly associated with the transportation paths. The second step determines the sequence of pickup and delivery tasks, while the third step corresponds to the schedule construction both for the acquisition unit and the hospital wards.

The results indicate immediate improvements when compared to the performance before the algorithms were applied. Not only have transportation paths been shortened by about 20%, more important is that the number of vertices labeled "single-serviced", which correspond to individual (non-integrated) task performance, were reduced by 62%. Due to satisfying the acquisition time limits, the on-going material flow and the coordination of working processes, the implementation of such a scheduling approach into a Slovenian hospital also suggests a more organized and reliable working environment. In addition to promising practical results, we believe that filling part of the gap detected in the topic literature might also be some contribution of this paper.

It is presumed that the proposed approach is relatively easily replicable in other similar hospitals that have both a limited transport network and need to collect medical samples from many locations while simultaneously have to guarantee timely deliveries of the samples to the laboratory. As a follow-up, one possibility is to modify the proposed algorithm for real-time scheduling problems, but its applicability depends on available hospital communication infrastructure. The proposed procedure could be improved by implementing more precise methods for transport request estimation. The latter mightbe modeled with different distributions, which affect the forecasting procedures and, consequently, the scheduling algorithm performance.

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