Workload Reduction Through Usability Improvement of Hospital Information Systems - The Case of Order Set Optimization

Research-in-Progress

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Abstract

Order sets are a critical component in hospital information systems and expected to reduce physician workload, substantially. Order sets represent time interval-clustered order items (e.g. medications prescribed at hospital admission) which are administered to patients during their hospital stay. We develop a mathematical programming model, an exact and a heuristic solution procedure with the objective to minimize physician workload associated with prescribing order sets. In a case study using order data on Asthma patients with severe conditions from a major pediatric hospital, we compare the hospital’s current solution with the exact and heuristic solutions on a variety of performance metrics. Our computational results reveal that using an interval decomposition approach substantially reduces computation times. Our physician workload analysis revealed that our exact approach reduces the hospital’s current workload for these patients from 12% to 65% simply by allowing 1 to 5 order sets in each time interval, respectively.

Keywords: Healthcare Information Systems, Health informatics/health information systems/medical IS, Analytical modeling, Heuristics
**Introduction**

The design of effective and efficient business processes through information and communication technologies (ICT) is an increasingly important problem, and healthcare is no exception (Barrett et al. (2015) and Bai et al. (2012)). Especially in hospitals where limited resources are available to meet high patient demand, streamlining processes is a challenge (Gartner and Kolisch (2014)). More significantly, along with process efficiency, improving patient safety and quality of care has been the target of recent research (Aron et al. (2011); Chen et al. (2011)). In this context, improving quality of care and disease management through ICT have been studied. Furthermore, as detailed data is increasingly available through exchange platforms on the individual level (Yaraghi et al. (2015)) the efficient management of tasks for individual patients becomes more and more relevant to improve workflow efficiency and quality of care, simultaneously.

Hospital information systems play an important role in the effective and efficient delivery of health care services. Within these systems, Computerized Physician Order Entry (CPOE) has proven to be effective in increasing patient safety, reduce medication errors and costs (Kini and Savage (2003)). Specifically, order sets support physicians in high risk situations by serving as expert-recommended guidelines, reducing prescribing time by making complex ordering easier, and increasing physician compliance with the current best practice. For instance, the ‘Asthma Admission Order Set’ groups together order items for Asthma patients upon admission. Size of order sets range from 2 to more than 50 unique items, and each item in order sets can be defaulted-ON or OFF according to clinical relevance and frequency of use. An order item can be part of multiple order sets. Despite the benefits of order sets, historical data indicate a tremendous variability in order set usage by physicians, driven largely by the diversity in patient population, physician experience, and system usability. Within CPOE, physicians can search for particular orders by typing the order names and the search result includes all a la carte orders and order sets that match the keyword because order set usage is not mandatory. A la carte orders are individual orders that physicians choose to enter without using order sets. Intuitively, ordering a la carte items takes more time compared to order sets because they have to be searched for and entered one by one. Some orders are standalone items and a la carte is the only way to prescribe them. Yet, reasons for ordering a la carte items instead of order set items mainly come from a physician’s disagreement with order set content, unfamiliarity with order sets, inconsistency of order set content with current best practices, and at times, a simple need for only one or two orders. Ordering efficiency decreases when order sets contain items that do not match the workflow or the patient’s condition, forcing physicians to go through long lists of orders to determine each item’s relevance to particular patients, and eventually rely on a la carte orders which are time-consuming and subject to errors (Zhang et al. (2014)).

This paper aims to address these challenges by proposing and testing an approach based on Discrete Optimization to create order sets from usage data with the objective of minimizing physicians’ workload. Physicians’ workload can be measured in mouse clicks, henceforth denoted as ‘mouse click costs’ (MCC). MCCs are associated with i) assigning patients to order sets, ii) deselecting non-required order items from order sets, iii) deselecting order items which are prescribed multiple times and iv) ordering items a la carte.

We formulate a mathematical program where dominance properties allow us to fix variables. We develop an exact and a heuristic solution procedure based on time interval decomposition. In contrast to solving sub-problems to optimality in our first algorithm, our second approach clusters order items heuristically to order sets by extending a well-known heuristic algorithm through mathematical programming. In a case study using order item data on Asthma patients with severe conditions from a major pediatric hospital, we compare the hospital’s current solution with the exact solutions on several performance metrics. Depending on the number of allowed clusters, our exact approach reduces physicians’ current workload for these patients from 12% to 65% simply by allowing 1 to 5 order sets in each interval, respectively. A detailed analysis of our solutions reveals a 72% drop-off in a la carte assignments which can be reduced even more by increasing the number of order sets. Extending our mathematical model and our experimental study to incorporate cognitive workload, associated with making critical ordering choices, is a promising future direction for this research.

The remainder of this paper is structured as follows. In the next section, we provide an overview of related work including clustering approaches that have been applied in the medical informatics domain. Afterwards, we provide a formal description of the problem and the model formulation. A brief computational study is provided in order to demonstrate the effectiveness of our approach based on data from a major hospital in the United States. In that section, we describe our evaluation metrics followed by a presentation of our results. We finally provide a conclusion and outline streams for further research.
Related Work

We focus on three relevant fields: Workflow management in healthcare, order set optimization and data-driven product development, and clustering methods.

Workflow Management in Health Care and Workload Impacts on Revenue and Care Quality

Hulshof et al. (2012) provide a recent literature review on planning decisions in health care including workflow management. More recently, Ceschia and Schaerf (2015) and Gartner and Kolisch (2014) improve patient scheduling decisions. Bai et al. (2012) improve IT-enabled processes in a pharmacological setting in which high risk situations can occur because of noisy data. Analytics approaches for chronic diseases and patient flow management are Bardhan et al. (2014) and Gartner (2015), respectively. Campbell et al. (2009) conclude that CPOE systems can have adverse effects on clinical workflows making it necessary to dovetail clinical workflows and information systems while Michtalik et al. (2013) observe that workload likely contributed to patient transfers, morbidity, or even mortality. Powell et al. (2012) study documentation tasks of clinicians and find out that over-worked clinicians document less and therefore hospital revenues are reduced.

Order Set Optimization and Data-driven Product Development

Related work on order set optimization includes Zhang et al. (2012b), Zhang et al. (2012a), Zhang et al. (2013) as well as Zhang et al. (2014). The authors employ heuristic methods to reduce physician workload in hospitals through order set improvement. Our study has a similar focus, however, we provide a mathematical model which guarantees the optimal development of order sets. Further extensions are, among others that workload associated with deselecting orders that are prescribed multiple times are incorporated. In addition, the result of our model implementation and tests based on real data provides us structural insights and bounds on the physician workload. Data-driven order set development has similarities to market-driven product development. Jiao et al. (2007) provide a review of product design approaches including applications of clustering techniques. More recently, Lei and Moon (2015) developed a market-driven product design approach by applying $k$-means clustering in the automobile industry. This is similar to our work since we develop order sets based on patient demand.

Clustering Approaches

Textbooks that cover clustering algorithms and other machine learning approaches are Bishop (2006) and Mackay (2003). Recent literature reviews are Baesens et al. (2009), Jain (2010), Meisel and Mattfeld (2010) as well as Olafsson et al. (2008). More specifically, the latter review mathematical methods applied to data mining which is highly relevant for our research. Similarly, Meisel and Mattfeld (2010) are relevant because they show the potential of clustering approaches from an application perspective. Hansen and Jaumard (1997) show how mathematical programming can be applied to clustering problems. One of the first binary programs to formulate clustering problems is based on Vinod (1969). Kulkarni and Fathi (2007) provide different models for a clustering problem and provide better integer programming relaxation-based lower bounds as compared to the standard linear programming relaxation. In their review, the authors provide the binary formulation as devised by Vinod (1969) and give an overview about algorithms such as the $K$-means algorithm (MacQueen et al. (1967)) which has been applied successfully to a variety of clustering problems. Focusing on healthcare, Cardoen et al. (2015) group medical items for surgeries which can be seen as a clustering problem. The difference to our problem is, among others, that we have a time interval-dependent demand function which captures the patients’ length of stay. With respect to the solution methodology, we can decompose the problem and solve subproblems to optimality or heuristically using $K$-means algorithm.

As a conclusion of our literature review, our study can be considered to be the first to successfully employ mathematical programming to order set optimization. In addition, we develop an exact and heuristic decomposition approach which allow us to solve real-world test instances. Finally, we compare our approaches on a variety of performance measures.

Problem Description and Model Formulation

In what follows, we provide a problem description followed by a mathematical model that clusters order items to which patients are assigned. We will use the following terms as synonyms: activities, items, orders, procedures and treatments.
Similarly, clusters and order sets are used as synonyms.

**Problem Description**

When patients arrive at the hospital and are treated over a planning horizon, we wish to assign these patients to clusters which represent sets of order items. Figure 1(a) in our experimental analysis section shows a screen shot of a sample order set. Unlike a la carte order placement, where users need to apply a mouse click every time to select an individual order, default ON items are automatically selected when an order set is chosen. With additional clicks, users can add default OFF items to the selection or deselect default ON items from the order placement (Zhang et al. (2014)). Since we assume that the selection of a default OFF order item has the same workload as compared to the selection of an a la carte item (both equals 1 click), our model formulation will not cover default OFF clustering and the associated switching decisions.

We now start with the definition of the general parameters for building clusters and then turn to patient-related parameters as well as workload 'cost' parameters for the assignment of patients' activities to order sets, and for selecting order items a la carte, among others.

**Set of Time Intervals, Clusters and Order Items**

We have a set of time intervals \( H := \{1, 2, \ldots, H\} \) with \( H \) that denotes the last interval, e.g. [22; 24] hours while intervals \( h, h' \in H \) are non-overlapping. Order sets can be created at each interval \( H \) and we index them using the set \( K := \{1, 2, \ldots, K\} \) with the maximum number of order sets denoted by \( K \). For example, \( K = 5 \) order sets can be created in each interval. Order items are denoted by set \( I_h := \{1, 2, \ldots, I_h\} \) in which \( I_h \) is the biggest index of order items observed in interval \( h \in H \).

**Patients, Patient’s Order Items and Click Costs**

Patient demand arriving in interval \( h \) is denoted by set \( P_h := \{1, 2, \ldots, P_h\} \) in which \( P_h \) is the last index of all patients in time interval \( h \). We observe activities that are required for patient \( p \) in interval \( h \) and we denote this subset by \( I_{p.h} \subset I_h \).

We denote \( c_{on} \) as costs when an order set is selected for a patient while \( c_{off,on} \) are costs when an order item that is part of an order set must be deselected for that particular patient because it is not required. If additional order items are required (in addition to the activities in an order set), costs of \( c_{off} \) arise for each additional activity. Sometimes, patients may be assigned to multiple order sets. In that case, it can happen that order items are prescribed multiple times and costs associated with the deselection of items that are prescribed multiple times are denoted by \( c_{off,mult} \). Selection cost for adding an a la carte item is denoted by \( c_{alc} \) and we assume that all costs are greater than zero.

**Model Formulation**

We will now introduce the decision variables, the objective function and the constraints to model the problem. The decision variables are shown in Table 1. We denote the \( a_{\text{on}}^{p,i,k} \) variables as ‘clustering variables’ because in each order set \( k \) (cluster) they will provide information which order item is defaulted ON. All other variables will mainly be used for assigning patients to order sets or performing decisions on the patients’ item level to determine the physician workload in our objective function.

<table>
<thead>
<tr>
<th>Decision variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a_{\text{on}}^{p,i,k} )</td>
<td>1, if order item ( i ) is defaulted ON in order set ( k ) in interval ( h ), 0 otherwise</td>
</tr>
<tr>
<td>( x_{\text{alc}}^{p,i} )</td>
<td>1, if patient ( p )’s order item ( i ) is chosen from a la carte items in interval ( h ), 0 otherwise</td>
</tr>
<tr>
<td>( x_{\text{off},on}^{p,i,k} )</td>
<td>1, if patient ( p )’s order item ( i ) is chosen from order set ( k ) in interval ( h ) is confirmed ON, 0 otherwise</td>
</tr>
<tr>
<td>( x_{\text{off},mult}^{p,i} )</td>
<td>1, if in interval ( h ) patient ( p )’s order item ( i ) is selected from defaulted ON in multiple order sets, 0 otherwise</td>
</tr>
<tr>
<td>( x_{\text{off,on}}^{p,i,k} )</td>
<td>1, if patient ( p )’s order item ( i ) is switched off from order set ( k ) and interval ( h ), 0 otherwise</td>
</tr>
<tr>
<td>( x_{\text{on}}^{p,i,k} )</td>
<td>1, if in interval ( h ) patient ( p ) is assigned to order set ( k ), 0 otherwise</td>
</tr>
<tr>
<td>( x_{\text{off},mult}^{p,i} )</td>
<td>1, if in interval ( h ) patient ( p ) is assigned to order set ( k ) and order ( i ) of that patient is defaulted ON, 0 otherwise</td>
</tr>
</tbody>
</table>

**Table 1. Overview of decision variables**
The model minimizes the total click costs for selecting a la carte items and order sets. Moreover, it accounts for deselecting activities from order sets to which activities are assigned because they are either not required or assigned more than one time. Finally, the selection of activities to order sets in which these activities are not part is penalized.

\[
\text{minimize } z = 
\sum_{h \in H} \sum_{p \in P_h} \left[ \sum_{i \in I_p, h} \left( c_{\text{alc}} \cdot x_{h,p,i}^{\text{alc}} + c_{\text{off,mult}} \cdot x_{h,p,i}^{\text{off,mult}} \right) + \sum_{h \in H} \sum_{p \in P_h} \sum_{k \in K} \left( c_{\text{off,non-req}} \cdot x_{h,p,k}^{\text{os,off,non-req}} + \sum_{i \in I_p \setminus I_{p,h}} \sum_{k \in K} x_{h,p,i,k}^{\text{off,non-req}} \right) \right]
\]

subject to

\[
x_{h,p,i}^{\text{alc}} + \sum_{k \in K} x_{h,p,i,k}^{\text{conf,on}} = 1 \quad \forall h \in H, p \in P_h, i \in I_p, h
\]

\[
x_{h,p,k} + x_{h,p,i,k}^{\text{os,off,non-req}} \leq 1 \quad \forall h \in H, p \in P_h, k \in K, i \in I : i \notin I_{p,h}
\]

\[
x_{h,p,k} - x_{h,p,i,k}^{\text{off,non-req}} \geq 0 \quad \forall h \in H, p \in P_h, k \in K, i \in I : i \notin I_{p,h}
\]

\[
x_{h,p,k}^{\text{alco}} - x_{h,p,i,k}^{\text{off,non-req}} \geq 0 \quad \forall h \in H, p \in P_h, k \in K, i \in I : i \notin I_{p,h}
\]

\[
x_{h,p,k}^{\text{os}} \geq x_{h,p,k}^{\text{alc}} + x_{h,p,k}^{\text{os}} - 1 \quad \forall h \in H, p \in P_h, k \in K, i \in I_{p,h}
\]

\[
x_{h,p,k} - x_{h,p,i,k}^{\text{conf,on}} \geq 0 \quad \forall h \in H, p \in P_h, k \in K, i \in I_{p,h}
\]

\[
x_{h,p,k}^{\text{alco}} - x_{h,p,i,k}^{\text{conf,on}} \geq 0 \quad \forall h \in H, p \in P_h, i \in I_{h,p,1}, k \in K
\]

\[
x_{h,p,k}^{\text{alco}} - x_{h,p,i,k}^{\text{off,non-req}} \geq 0 \quad \forall h \in H, p \in P_h, i \in I : i \notin I_{p,h}, k \in K
\]

\[
x_{h,p,k}^{\text{alco}} \in \{0, 1\} \quad \forall h \in H, p \in P_h, k \in K
\]

\[
x_{h,p,k}^{\text{alc}} \in \{0, 1\} \quad \forall h \in H, p \in P_h, i \in I_{p,h}
\]

\[
x_{h,p,i}^{\text{alc}} \in \{0, 1\} \quad \forall h \in H, p \in P_h, i \in I_{p,h}
\]

\[
x_{h,p,k}^{\text{off,mult}} \in \{0, 1\} \quad \forall h \in H, p \in P_h, i \in I : i \notin I_{p,h}, k \in K
\]

\[
x_{h,p,k}^{\text{conf,on}} \in \{0, 1\} \quad \forall h \in H, p \in P_h, i \in I_{p,h}
\]

\[
x_{h,p,k}^{\text{off,non-req}} \in \{0, 1\} \quad \forall h \in H, p \in P_h, i \in I_{p,h}
\]

Objective function (1) minimizes click costs for selecting patients’ order items from a la carte, deselecting order items which are prescribed multiple times, assigning patients to order sets and deselecting non-required but defaulted ON order items from order sets. In our experimental analysis, we will break down the results by the four parts of the objective function, see Figures 1(b)–(d) and denote them as $z(\text{alc})$, $z(\text{off,mult})$, $z(\text{os})$, $z(\text{off,non-req})$, respectively. Constraints (2) ensure that each patient’s required order item is either selected a la carte or it is selected from order sets. If it is selected from order sets, the order item is confirmed as defaulted ON. Constraints (3) ensure that if a patient is assigned to an order set and a non-required order item is defaulted ON, then it has to be de-selected. Constraints (4) ensure that if a patient’s non-required order item is switched off from defaulted-on, it has to be defaulted-on in the corresponding order set. Constraints (5) ensure that if the patient is assigned to an order set and the order item is defaulted-on, the assignment variables have to be 1. Constraints (6) ensure that if the patient’s required order item is selected multiple times, it has to be counted by the auxiliary decision variables. Constraints (7) ensure that a patient’s required order item can only be confirmed on if it is defaulted-on in the corresponding order set. Constraints (8) ensure that if a patient’s order item is switched off from defaulted-on in an order set, the patient has to be assigned to the corresponding order set. Constraints (9) ensure that if a patient’s defaulted-on order item is switched off, the patient has to be assigned to the corresponding order set. (10)–(14) are the decision variables and their domain.

**Dominance and Fixing Variables**

**Proposition 1.** Let $c_{\text{alc}} < (c_{\text{os}} + c_{\text{off,non-req}})$. For any demand pattern that fulfills $|I_{p,h}| \leq 2$, choosing $\forall i \in I_{p,h}$ from a la carte is optimal. This allows us to fix a la carte and order set assignment variables $x_{h,p,i}^{\text{alc}}$ and $x_{h,p,k}^{\text{os}}$, respectively.
Proof. Let \( H = \{1\}, I_1 = \{1, 2\}, P_1 = \{1\}, I_{1, 1} = \{1\}, K = \{1\}, a_{1, 1, 1} = a_{1, 2, 1} = 1 \). Select order set \( k = 1 \) for patient \( p = 1 \) (1 click), de-select non-required order \( i = 2 \) (1 click). As a consequence, \( x_{1, 1, 1} \cdot x_{1, 2, 1} \cdot x_{1, 1, 2} \cdot x_{1, 2, 1} \cdot x_{1, 1, 1} \cdot x_{1, 2, 1} \). □

An Exact and a Heuristic Solution Approach Based on Time Interval Decomposition

The absence of time interval-connectivity allows us to solve each time interval independently using Algorithm 1(a)–(b). As can be seen, instead of solving the entire model (1)–(14), we solve it for each time interval independently and to optimality (a). Our heuristic (b) has similarities to the heuristic devised by Zhang et al. (2014). Their forward search optimizes time interval start- and end-points while in each iteration, the \( K \)-means algorithm is used to create clusters. Then, for each patient, they rank potential order set assignments to patients and assign the order set with the lowest total, we observed

\[
\sum_{h \in H} z_h
\]

We evaluated our approaches on data from a major U.S. university hospital and focused on ‘Asthma major’ patients. In the current system, 24 unique order sets were used along with a la carte orders while the total number of unique order items in the CPOE system come up to 3,335. We joined usage data from the current CPOE system with data from the electronic medical record. In doing so, we obtained time stamps for the current order set assignments and patient demand, among others. This allows us to generate all parameters for our exact and heuristic approaches and to compare the solution with the physicians’ current workload.

Experimental Analysis on Asthma Major Patients

Data

We evaluated our approaches on data from a major U.S. university hospital and focused on ‘Asthma major’ patients. In total, we observed 15 patients who were prescribed 1, 150 order items within 24 hours before and after admission. In the current system, 24 unique order sets were used along with a la carte orders while the total number of unique order items in the CPOE system come up to 3,335. We joined usage data from the current CPOE system with data from the electronic medical record. In doing so, we obtained time stamps for the current order set assignments and patient demand, among others. This allows us to generate all parameters for our exact and heuristic approaches and to compare the solution with the physicians’ current workload.

Analysis of Computation Time and Optimality Gap

All computations were performed on an Intel Core i7-4700MQ CPU with 32 GB RAM running Windows 7 operating system. The models were coded in Java in an ILOG Concert environment. The solver used was ILOG CPLEX 12.4 (64 bit) and we used the \( K \)-means algorithm as implemented in WEKA (Witten and Frank (2011)). We chose to split the planning horizon into \( H = 9 \) intervals as follows: \([-24, -4.45], [-4.45, -2], [-2, 0], [0, 1], [1, 2], [2, 5], [5, 10], [10, 15] \) and \([15, 24]\) hours with respect to the admission time. The rationale for setting these intervals is because it ensures that at least 10 patients exist in each interval. Also, intervals shouldn’t be too small because otherwise, physicians would have to revise the order sets. Similarly to Zhang et al. (2014) we ensure that the admission interval starts exactly at time 0. We chose to set the cost coefficients \( c_{alc} = c_{os} = c_{off, non\text{-}req} = c_{off, mult} = 1 \). In doing so, we measure the physicians’ workload associated with their mouse clicks and frame it as mouse click costs (MCC). To evaluate the computational complexity, we vary the number of order sets using \( K = 1, 2 \) and 5.
Table 2 shows the number of variables, constraints and the computation times broken down by number of order sets $|\mathcal{K}|$ and each of our approaches. For the decompositions, we report the average number of variables and constraints for the subproblems. The figures reveal that the full model formulation fails to provide an optimal solution for $K = 5$ clusters within 2 hours computation time. More specifically, the optimality gap is almost 40%. However, by decomposing the model, approximately 5 minutes are required to guarantee optimal order sets.

| Approach       | $|\mathcal{K}|$ | $z$ | # Decision variables | # Constraints | Computation time [ms] | Optimality gap [%] |
|----------------|----------------|-----|----------------------|---------------|-----------------------|-------------------|
| Model (1)-(14) | 1             | 878 | 12,078               | 25,928.0      | 6,379                 | 0.0               |
|                | 2             | 686 | 21,856               | 49,556.0      | 350,821               | 0.0               |
|                | 5             | 517 | 51,190               | 120,440       | 7,200,000             | 39.6              |
| Algorithm 1(a) | 1             | 878 | 1,342.0              | 2,880.9       | 2,849                 | 0.0               |
|                | 2             | 686 | 2,428.4              | 5,506.2       | 13,875                | 0.0               |
|                | 5             | 352 | 5,687.8              | 13,382.2      | 316,696               | 0.0               |
| Algorithm 1(b) | 1             | 1,035| 1,342.0             | 2,952.0       | 305                   | 17.9              |
|                | 2             | 908 | 2,428.4              | 5,648.4       | 475                   | 32.5              |
|                | 5             | 727 | 5,687.8              | 13,737.8      | 1,004                 | 106.5             |

Table 2. Computation time analysis results

**Physician Workload Analysis**

Figure 1(b) provides an analysis of physician workload in the current solution. We observed in the current solution that order items were defaulted-off and switched from off to on which we denote by $z$(off,on). Similar to the computational analysis, we set $K = 1, 2$ and $5$. The figures reveal a substantial drop-off between the current workload observed at the hospital and the optimal solution simply by allowing $K = 1$ order set. Another observation is that the physician workload associated with the selection of order sets increases while the number of a la carte item selections decreases. A more detailed analysis of the results revealed that the current workload can be reduced from 12% to 65% by allowing 1 to 5 order sets in each interval, respectively while a 72% drop-off in the use of a la carte order items can be observed. Using our heuristic (Algorithm 1 (b)), we observe a significant use of a la carte items especially when $K = 1$. A detailed analysis of $K$-means in interval $[-24, -4.45]$ using $K = 1$ revealed that the centroid’s values are 1 if more than 50% of the patients required the corresponding order item.

Figure 1. Pneumonia admission order set (Zhang et al. (2014)) (a), current order set usage (b), optimal (c) and heuristic order set optimization (d)
Order Set Size and Number of a La Carte Selections

For each time interval $h$, we now report the average order set size ($\text{OSS}_h$) and a la carte selection count ($\text{ALC}_h$). The metrics are computed as $\text{OSS}_h = \sum_{i \in I_h} \sum_{k \in K} a_{i,k}^h / |K|$ and $\text{ALC}_h = \sum_{p \in P_h} \sum_{i \in I_{p,h}} x_{h,p,i}$ for interval $h \in \mathcal{H}$. Table 3 shows the results for both metrics. The figures reveal that in the current solution, the order set sizes are substantially smaller than in the optimal or heuristic approach. Another observation is that in the optimal solution, order set sizes are larger as compared to the heuristic solution.

<table>
<thead>
<tr>
<th>$h$</th>
<th>Time</th>
<th>Current</th>
<th>Algorithm 1(a)</th>
<th>Algorithm 1(b)</th>
<th>Algorithm 1(a)</th>
<th>Algorithm 1(b)</th>
</tr>
</thead>
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<td>156</td>
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</tr>
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<td>17</td>
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<td>53</td>
<td>0.0</td>
</tr>
<tr>
<td>9</td>
<td>[15, 24]</td>
<td>0.0</td>
<td>71</td>
<td>14</td>
<td>61</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Table 3. Order set size (OSS) and number of a la carte selections (ALC)

Summary and Conclusions

In this paper, we have introduced an exact and extended a heuristic method based on mathematical programming for order set optimization to improve workflows within Hospital Information Systems. We have shown that physician workload associated with order set usage can be decreased substantially as compared to current hospital practice using our approaches. Depending on the number of allowed clusters, our exact approach reduces physicians’ current workload for these patients from 12% to 65% simply by allowing 1 to 5 order sets in each time interval, respectively. A detailed analysis of our solutions reveals a 72% drop-off in a la carte assignments which can be reduced even more by increasing the number of order sets. Extending this model to incorporate cognitive processing costs in the objective function, associated with costs for making critical ordering choices for each individual order item and evaluating the increase in quality of care are promising future directions for this research.

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