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A Robust Optimization Method for Service Quality Improvement in Health Care Systems under Budget Uncertainty

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***Abstract*—**With the development of business competition, it is important for healthcare providers to improve their service qualities. In order to improve service quality of a clinic, four important dimensions are defined: tangibles, responsiveness, empathy, and reliability. Moreover, there are several service stages in hospitals such as financial screening and examination. One of the most challenging limitations for improving service quality is budget which impressively affects the service quality. In this paper, we present an approach to address budget uncertainty and provide guidelines for service resource allocation. In this paper, a service quality improvement approach is proposed which can be adopted to multistage service processes to improve service quality, while controlling the costs. A multi-objective function based on the importance of each area and dimension is defined to link operational variables to service quality dimensions. The results demonstrate that our approach is not ultra-conservative and it shows the actual condition very well. Moreover, it is shown that different strategies can affect the number of employees in different stages.

***Keywords*—**Service quality assessment, healthcare resource allocation, robust optimization, budget uncertainty.

I. Introduction

THE attainment of quality in products and services has become a pivotal concern since 1980s because of competition between companies. While quality in tangible goods has been described and measured by marketers, quality in services is largely undefined. In other words, when purchasing goods, the consumer employs many tangible cues to judge quality like style, hardness, color, and label. When purchasing services, fewer tangible cues exist and, in most cases, tangible evidence is limited to the service provider's physical facilities, equipment, and personnel. That being so, in order to raise customer satisfaction with the service received, there are other kinds of evaluation like responsiveness, reliability, access, courtesy, etc. [1]-[3].

Patient satisfaction is one of the most important factors that affect quality of service in hospitals [4]. With rapid increase in demand for healthcare services and patients' service quality expectations, it is important for health care providers to develop efficient healthcare systems and improve their service quality [5], [6]. Healthcare service quality highly depends on service process and the interactions between customers and service provider [7]. Since healthcare service is an intangible product, it is more difficult to define and measure quality than in other sectors [8].

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A health-care system, like hospital, has specific dimensions for evaluation of service quality which has been categorized to three groups by [9]. The most important dimensions for health-care system are tangibles (i.e., physical facilities, appearance of personnel, tools, etc.), responsiveness (i.e., willingness and readiness of employees to provide specific service), empathy (i.e., understanding the needs of costumer), and reliability (i.e., performance and behavior of providers). Moreover, there are several service stages in hospitals including financial screening, examination, surgery, etc.

There are some uncertainties in the observations that affect service quality of a healthcare system. Some studies integrated the service quality method with fuzzy method to determine hospitals' policy by prioritizing attributes that have a big gap to improve the quality of its services [4], [10], [11]. Robust optimization techniques also have been used to deal with uncertainties in different healthcare planning problems [12]-[16]. Decision makers need to make a trade-off between achieving high service quality and controlling its costs. In this paper, we present a service quality improvement approach that can be adopted to multistage service processes and the goal is to improve service quality (SQ), while controlling the costs.

The rest of this paper is structured as follows: Section II contains the mathematical modeling and robust optimization settings. Section III describes our numerical experiments. Then, our conclusions are presented in Section IV.

II. Problem Definition

In this paper, we want to improve the SQ of hospital in terms of controlling the financial budget and costs under uncertainty over the parameters. This approach is applicable to all kinds of places where you want to improve the quality along with the controlling the cost and make operational decisions like the number of employees and the amount of training they need to have based on their expertise. What you need for this purpose is determining the sections where you want to improve the SQ and collecting data from that specific hospital to be processed and used like the relation between the operational variables and SQ dimensions in different stages in health-care system like maternity section, microbiology, surgery room, emergency room, etc., and the relation between the service characteristics of each stage with the considered operational variables. The improvement of SQ for each stage and maximizing the overall SQ is our goal. So, we also need to know the total importance of each stage and the importance of each dimension in each stage separately. These kinds of parameters depend on the managerial strategies used in the health-care systems.

III. Solution Approach

Based on the problem definition, we define the following the following notations and general model:

A. General Parameters and Decision Variables

- w_j: the importance weight of stage j
- d_{ij}: the importance weight of SQ dimension i in stage j
- A_{ij}: the matrix of model parameters relating operational variables to SQ dimension i for stage j
- B_{ij}: matrix of model parameters relating operational variables to service system characteristics for stage j
- C_j: model parameters reflecting stage j characteristics,
- Ksi: the cost of training each hour for SItrain
- Kcd: the cost of training each hour for CDtrain
- E: the amount of training budget,
- E': the amount of service budget.
- D_j: cost for all operational variables in stage j,
- x_j: operational variables for stage j
- y_{j_i}: SQ dimension of i for stage j: 7-point scale: 1 poor, 7 excellent.
- n_j: number of employees of stage j
- $CDtrain_j$: the amount of Cultural Diversity Training the provider received during the last year in days for stage j
- $SItrain_j$: The amount of Service Training the provider received during the last year in days for stage j.

B. General Mathematical Model

$$max_y \sum_i^n \sum_j^m w_j d_{ij} y_{ij} \tag{1\_a}$$

$$s.t. A_{ij} x_i = y_{ij} \quad \forall i, j \tag{1\_b}$$

$$\sum_i^n B_{ij}\, x_j = C_j \qquad \forall j \tag{1\_c}$$

$$\sum_i^n D_j\, x_j \le E' \tag{1\_d}$$

$$\sum_i^n (Kcd\, CDtrain_j + Ksi\, SItrain_j) n_j \le E \tag{1\_e}$$

$$0 \le x_j \le UB_j, \quad \forall j \tag{1\_f}$$

$$0 \le y_{ij} \le 7, \ \forall i, j \tag{1\_g}$$

$$0 \le n_j \le ub, \qquad \forall j \tag{1\_h}$$

$$LB \le CDtrain_j, SItrain_j \le UB \tag{1\_i}$$

The objective function (1_a) maximizes the overall SQ based on the importance weights. The combination of operational variables constitutes each dimension based on their correlation in constraint (1_b). As an example, the waiting time for appointment with the doctor in examination area or the duration of appointment is two of the operational variables that determine the responsiveness dimension. Also, the operational variables like number of tools, mop time, bath time have relation with each other in system which is presented in constraint (2_b). The characteristic of each stage is shown in constraint (1_c). The budget limitations' constraints are (1_d) and (1_e).

IV. Uncertainty over the Budget Constraint's Parameters

This problem is nonlinear model because of Training Budget constraint. It is important to know that the $CDtrain$ and $SItrain$ variables in training budget constraint have normal distributions with known means and standard deviations. This issue helps to change the problem to linear problem and put the means of these two variables as the uncertain parameters. That being so, the budget constraint changes to following equation for the general model:

$$\sum_j^m \left(Kcd\, \overline{CDrain_j} + Ksi\, \overline{SItrain_j}\, \right) n_j \le E \tag{2}$$

A. Robust Optimization Parameters & Variables

- z_{j_i}: the random variable which is associated with the uncertain data.
- Γ: the uncertain (*parameter*) adjust the robustness of model against the level of conservatism of the solution and restricting the number of parameters whose values deviate from the nominal value,
- p: dual parameter of robust optimization formulation or slack variable of $\sum_i z_{j_i} \le \Gamma$,
- q_{j_i}: dual parameter or slack variable of this constraint $0 \le z_{j_i} \le 1$.

We have uncertain data for our parameters. In real-world applications of Linear Programming, one cannot ignore the possibility that a small uncertainty in the data can make the usual optimal solution completely meaningless from a practical viewpoint. So, we protect against violation of this constraint deterministically by robust optimization solution.

$\widehat{SItrain_j}$ and $\widehat{CDtrain_j}$ are equal to $(2 * SD)$ of each stage and the range of their change are $[\overline{SItrain_j} - \widehat{SItrain_j}$, $\overline{SItrain_j} + \widehat{SItrain_j}]$ and $[\overline{CDtrain_j} - \widehat{CDtrain_j}$, $\overline{CDtrain_j} + \widehat{CDtrain_j}]$ for $2m$ variables or uncertain parameters. Associated with the uncertain parameters, random variables $z_{j_i} = \frac{\widehat{a_{j_i}} - a_{j_i}}{\widehat{a_{j_i}}}$ are defined which avoid an unknown but symmetric distribution and takes values in [-1,1].

Under the model of data uncertainty, when we add these new constraints into the general model, the robust formulation would be created as follows:

$$\begin{gathered} \sum_j^m (Kcd\, \overline{CDtrain_j} + Ksi\, \overline{SItrain_j}) n_j + \\ \max_z \sum_{j_i}^{2m} (Kcd\, \widehat{CDtrain_j}\, z_{j_i} + Ksi\, \widehat{SItrain_j}) n_j z_{j_i} \le E \\ \sum_k^{2m} z_{j_i} \le \Gamma, \ 0 \le \Gamma \le 2m \end{gathered} \tag{3}$$

$$0 \leq z_{j_i} \leq 1 \; \forall j_i = 1,..,2m$$

Using strong duality theorem, we can replace the nonlinear constraint (3) with following tractable linear constraints for all T values.

$$\sum_j^m (Kcd\ \overline{CDtrain_j} + Ksi\ \overline{SItrain_j}) n_j + \Gamma p + \sum_{j_i=1}^{2m} q_{j_i} \leq E$$
$$p + q_{j_1} \geq Kcd\ \widehat{CDtrain_j}\ \forall\, j_1$$
$$p + q_{j_2} \geq Kcd\ \widehat{CDtrain_j}\ \forall\, j_2$$
$$p, q_{j_i} \geq 0\ , \forall j_i = 1,..,\Gamma$$

So, we can easily solve this problem with off-the-shelf solvers as a linear problem.

V. Numerical Experiments

We consider four SQ dimensions including tangibility, responsiveness, empathy, and reliability & assurance and two stages including examination area and financial screening area. We assume $CDtrain$ and $SItrain$ are parameters with uncertainty in the training budget constraint. In addition to the number of employees, there are other critical operational variables for these two stages such as physicians, physician assistants, nurse practitioners, training hours, waiting time for getting service, duration time of service, and the cleaning time (i.e., mop time, and bath time).

TABLE I
Optimal Solutions for Different Uncertainty Budget

Model	Deterministic		Γ = 1		Γ = 2		Worst-case	
Variables	S1	S2	S1	S2	S1	S2	S1	S2
Reliability	5.90	6.10	5.85	6.05	5.80	6.00	5.75	5.90
Responsiveness	6.20	6.30	6.19	6.24	6.10	6.20	6.05	6.15
Empathy	6.30	6.35	6.12	6.31	6.08	6.00	6.00	5.90
Tangibility	5.90	5.95	5.88	5.93	5.85	5.90	5.80	5.88
# of employees	5	12	4	11	4.	10	4	9
SQ	6.12		6.07		5.99		5.92	

The data we used for this paper are gained from [1]. In Table I, we have optimal solutions for different uncertainty budgets (Γ) where the importance of stages and different dimensions are equal. As can be seen, the higher the uncertainty budget is, the less the total SQ we have. Accordingly, the best result is achieved from the model with Γ = 1, which is neither ultra-conservative nor non-realistic.

In Table II, three different strategies are compared where the uncertainty budget equals to 1. In the first case, we assume that the hospital's priorities are more reliability and empathy dimensions in examination area and the result shows the greater number of employees because the effect of our priorities on the number of employees. In two other cases where the priorities are other two dimensions, the number of employees is less than before. However, their difference is not significant because of budget limitations.

TABLE II
Optimal Solutions for Different Mentioned Cases

Model	Case 1		Case 2		Case 3	
Variables	S1	S2	S1	S2	S1	S2
Reliability	5.90	6.10	5.80	6.00	5.50	6.15
Responsiveness	6.00	6.20	6.22	6.24	6.10	6.30
Empathy	6.20	6.35	6.10	6.20	6.10	6.40
Tangibility	5.60	5.80	5.90	6.00	5.80	6.04
# of employees	5	12	4	11	4	12
Service quality	6.018		6.05		6.048	

VI. Conclusion

We can conclude that our robust approach could handle the uncertainty challenges related to budget limitations in the healthcare system service quality. This approach is neither ultra-conservative like the worst-case problem, nor nonrealistic where we do not consider uncertainty parameters. Moreover, the importance of stages and service quality dimensions can affect the number of employees we assign to different stages. On the other hand, because of the budget limitations, we are restricted to assign significantly more employees.

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