IIE Transactions on Healthcare Systems Engineering (2014) **4**, 80–87

ISSN: 1948-8300 print / 1948-8319 online
DOI: 10.1080/19488300.2014.904456

Resource allocation decision making in the military health system

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Received December 2013 and accepted March 2014

The necessity to efficiently balance and re-allocate system resources among hospitals in a hospital network is paramount, especially as health systems experience increasing demand and costs for health services. In this paper, we proffer a resource allocation-based optimization model that adjusts resources (system inputs) automatically, which provides decision makers (such as health care managers and policy-makers) with a decision-support tool for re-allocating resources in large health systems that are centrally controlled and funded, such as the Military Health System. In these systems, inputs are fixed at certain levels and may only be adjusted within medical treatment facilities, while outputs must be maintained. We provide a mathematical formulation and example solutions from a case study using real-world data from sixteen U.S. Army hospitals. We also find utility in the use of multi-start evolutionary algorithms to store multiple optimal solutions for consideration by decision makers.

Keywords: Resource allocation, multi-criteria optimization, healthcare management, decision analysis, military medicine

1. Introduction

As the growth in health care costs continues, large, centrally funded and operated healthcare systems, such as the Department of Defense's Military Health System (MHS), must become more efficient. The MHS operates a $52 billion system that provides health services to over 4.5 million enrolled beneficiaries such as uniformed service members, their family members, survivors, and retirees (MHS Stakeholder's Report, 2012). Due to these rising health care costs, the MHS must determine new methods of analysis to efficiently allocate (and re-allocate) resources by balancing costs, quality of care, workload, patient satisfaction, and access to care across the MHS. To do so requires careful management of major health system components.

The MHS is centrally funded, which means that dollars are sent to hospitals for expenditure. The amount of money provided to each hospital varies based largely on historical expenditures. Recently, the efficiency of hospitals within the MHS has received quite a bit of attention from leaders (Coppola *et al.*, 2012), and the concern for improving health system performance motivates this study.

The application of resource allocation and efficiency measurement techniques to military health systems is a rarity. Charnes *et al.* (1985) were the first to use data envelopment analysis (DEA) in their evaluation of the performance of 24 Army health care facilities. They selected traditional workload criteria for analysis of outputs including the number of personnel trained, relative weighted product (RWP, a weighted inpatient workload metric), and clinic visits, which are considered traditional elements of production in health care. For inputs in their DEA model, they evaluated full time equivalent (FTE) employees by specific category, inpatient expenditures, outpatient expenditures, weighted procedures, occupied bed days, and operating room hours.

Following this first study, Mihara (1990) used both DEA and ordinary least squares (OLS) regression methods to conduct an efficiency analysis of the utilization of personnel at Navy medical treatment facilities for resource allocation decisions. The results of the study were used to baseline both physician requirements (workload and beneficiary dependent) and professional staff requirements (physician dependent). His study was limited in that the analyses were driven by only raw workload metrics, and

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did not include other measures such as personnel readiness, prevention and training.

Ozcan and Bannick (1994) conducted a longitudinal study of 124 Department of Defense hospitals to evaluate trends in hospital efficiency based on data from the American Hospital Association Survey. This study was conducted at the strategic-level with little actionable information. Coppola (2003) used DEA to evaluate 78 treatment facilities using data from 1998 to 2002. For model input variables, he used costs, number of beds in the treatment facilities, FTEs, and number of services offered. For model output variables, he used surgical visits, ambulatory patient visits (APV), emergency room visits, case mix adjusted discharges (CMAD), RWP and live births. As a limitation of his analyses, Coppola focused on workload as the primary measure for efficiency rather than the standardized outpatient workload metric called relative value units (RVUs), which captures the complexity of workload by accounting for resource consumption.

Piner (2006) used DEA to evaluate clinical efficiency of 49 obstetric clinics at various treatment facilities and found that there was significant variability in the level of staffing and expenses among the clinics; this variability suggested inconsistencies in management across the clinics. The Army performed the highest in terms of average efficiency score, followed by the Air Force and then the Navy. Piner also compared the size of the treatment facilities, which revealed that larger hospitals were more efficient than smaller hospitals.

Fulton *et al.* (2007) developed decision-support tools for performance-based resource allocation. Specifically, they used DEA and stochastic frontier analysis (SFA) to illustrate the feasibility of incorporating technical efficiency considerations in the funding of Army hospitals and identified the primary cost drivers for Army hospital operations. Using a three-variable, logarithmic-linear model, they found that $120 million could be re-allocated to improve Army hospital performance. Fulton *et al.* (2008) investigated military hospital cost models that incorporated quality, access and efficiency to provide decision-support for resource forecasting in the MHS. In their analyses, they used OLS regression estimation, ridge regression and robust regression methods to evaluate logarithmic-linear cost models that included DEA efficiency scores. They demonstrated that military hospital resource allocation models should include quality and efficiency as components along with the traditional elements of complexity-weighted inpatient and outpatient workload.

1.1. *Motivation and purpose*

Although the previous literature highlighted how efficiency measurement techniques such as DEA, SFA and OLS were used to help optimize system performance of the MHS, none of these studies addressed how the MHS components are intrinsically linked in a complex, multiple objective fashion. Further, none of these studies provided decision-support for the automatic re-allocation of resources (system inputs). Thus, the motivation for this study is then the necessity to efficiently balance resources among hospitals in large health systems that are centrally controlled and funded while sustaining system output objectives. Senior military decision makers of the MHS seek to minimize inputs (specifically budgeted dollars and full-time equivalent healthcare providers) while maintaining outputs (such as outpatient weighted workload, inpatient weighted workload, prevention metrics, access to care metrics, and patient satisfaction) constant.

Because our motivating example from the MHS consists of multiple competing objectives (cost, quality, satisfaction, and workload), we should first understand some basic concepts from multiple criteria mathematical programming (MCMP) and DEA, which are optimization methods from the discipline of multiple-criteria decision-making (MCDM) typically employed for resource allocation decision-making. In MCMP, we have a set of functions that define all objectives to be maximized (or minimized). The problem, however, is that conflicting goals (or criteria) prevent the simultaneous optimization of all the objectives. Since the objective functions are conflicting in that no single ideal solution can be achieved, there exists a set of efficient (also called Pareto optimal or non-dominated) solutions. Here, an efficient solution is such that one can improve an objective only at the expense of at least one other objective, where a dominated solution is such that one can improve an objective without losing achievements in other objectives.

On the other hand, DEA is a set of flexible, mathematical programming approaches for the assessment of technical efficiency, where efficiency is often defined as a linear combination of the weighted outputs divided by a linear combination of the weighted inputs. In DEA, we assume that an organization wishes to assess the relative efficiencies of some set of comparable subunits (known as Decision Making Units or DMUs). For each DMU, there is a vector of associated inputs and outputs of managerial interest. A DMU that has an efficiency score of one and a zero-slack solution (for all slacks) is considered technically efficient, which is attained only if it is impossible to improve any input or output without worsening some other input or output. In all other cases, it is possible to improve one or more of the inputs or outputs without worsening any other input or output. In DEA, weights are determined via optimization, while in MCMP, these weights are generally assigned (preemptive or non-preemptive).

In the case of both MCMP and DEA optimization approaches, the evaluation of system slack informs decision makers how to adjust inputs, but not how the slack should be efficiently re-allocated. Moreover, the dual variables (shadow prices) show the effects of unit relaxation in constraint (e.g., inputs) might have on the objective function, although inputs in these large systems are largely fixed. Further, sensitivity analysis associated with adjustments in any portion of the model can help inform decision makers. Nevertheless, no amount of traditional manipulation of MCMP and DEA models provides decision makers clear recommendations about how to re-allocate system input resources to achieve the highest level of performance possible (efficiency).

1.2. *Overview*

In fixed input health systems such as the MHS, it becomes necessary to improve system performance by re-allocating inputs among the existing DMUs, as decision makers seek to re-balance funding (cost) and personnel across the system. Doing so requires decision-support to identify "winners" and "losers."

Because the evaluation of slack and reduced costs in traditional MCMP and DEA model formulations does not provide sufficient re-allocation decision-support, we leverage the structural similarities in these two MCDM methods (see Joro *et al.*, 1998; Korhonen and Syrjanen, 2004; Fulton *et al.*, 2013) to develop a hybrid resource allocation-based optimization model that helps the decision-maker balance competing objectives automatically. A multi-objective optimization model that adjusts resources automatically across all treatment facilities to achieve maximum system efficiency would (at a minimum) provide decision-support and insight for leaders interested in evaluating multiple objectives simultaneously.

For these reasons, we offer an optimization model that evaluates efficiency and provides multi-criteria decision-support for resource re-allocation within a hospital system. This model is important for health systems that must operate with fixed budgets and personnel authorizations, such as the Military Health System. This optimization model assumes that the decision-maker would like to re-allocate inputs in order to have the resources necessary to achieve at least a minimum level of performance.

2. Methods

Although DEA and MCMP are related optimization methods for evaluating efficiency in multiple objective problems, the use of either approach does not provide sufficient decision-support for optimizing system performance when inputs are fixed. Therefore, we propose a Multi-Objective Auto-Optimization Model (MAOM) for specific cases where health system decision makers seek to balance system components that might be interpreted as a performance ratio (not necessarily efficiency). As in our motivating example concerning the Military Health System, such a model formulation should be able to identify inputs that might be manipulated (re-allocated) to improve system performance over multiple outputs (objectives).

Essentially, this resource allocation-based optimization model should be able to provide sensitivity analysis to advise decision makers how to optimally re-allocate system input resources in order to attain the most efficient system possible. Thus, the next model formulation applies to multi-objective optimization problems (MOOP) that involve inputs that are fixed but can vary between DMUs. In the fixed budget MHS, for example, we may re-allocate system input resources among its existing facilities.

A description of the model, its derivation, and an application follow. The definition of variables, sets, and data matrices follows.

Indices

i = index of all m DMUs (i.e. hospitals)
j = index for outputs
k = index for inputs

Decision Variables

δ_{ki} = adjustments to each input k by DMU i with $\delta \in \Delta$
α_{ji} = weight for output j and DMU i with $\alpha \in \mathrm{A}$
λ_{ki} = weight for input k and DMU i with $\lambda \in \Lambda$
r = lower limit for efficiency score required for all DMUs

Data

x_{ki} = input k for DMU i with $x \in \mathrm{X}$
y_{ji} = output j for DMU i with $y \in \mathrm{Y}$

MAOM Formulation

$$Max\, z = \sum_i \sum_j \alpha_{ji} y_{ji} \tag{1}$$

Subject to:

$$r \leq \sum_j \alpha_{ji} y_{ji}, \forall i \tag{2}$$

$$\sum_j \alpha_{ji=v} y_{ji} - \sum_k \lambda_{ki=v}(x_{ki} + \delta_{ki}) \leq 0, \forall i, v \in \{1, 2, ..N\} \tag{3}$$

$$\begin{aligned} \sum_k \lambda_{ki}(x_{ki} + \delta_{ki}) &= 1, \forall i && (4) \\ x_{ki} + \delta_{ki} &\geq 0, \forall k, i && (5) \\ \sum_i \delta_{ki} &= 0, \forall k && (6) \\ 0 \leq r &\leq 1 \\ \alpha_{ji} &\geq 0 \forall j, i \\ \lambda_{\mathrm{ki}} &\geq 0 \forall k, i && (7) \\ \delta_{ki} &\text{ free } \forall k, i \end{aligned}$$

The objective function (1) seeks to optimize the sum of the efficiencies for all of the DMUs, which are the weighted outputs in this MAOM model. In (2), the weighted outputs are restricted to be greater than or equal to a global efficiency variable r, which exists on [0, 1]. This constraint is important as one could imagine the objective function seeking to reduce the efficiency of one DMU to near zero in order to make the others nearer to one.

In (3), we force the sum of the weighted outputs to be less than or equal to the sum of the weighted inputs after adjusting them up or down by the amount necessary to

Table 1. Data for textbook healthcare example

Hospital	FTEs	Supply Expenses	Available Bed Days	Patient Days > = 65	Patient Days <65	Nurses Trained	Interns Trained
A	310.0	134.6	116.0	55.31	49.52	291	47
B	278.5	114.3	106.8	37.64	55.63	156	3
C	165.6	131.3	65.52	32.91	25.77	141	26
D	250.0	316.0	94.4	33.53	41.99	160	21
E	206.4	151.2	102.1	32.48	55.3	157	82
F	384.0	217.0	153.7	48.78	81.92	285	92
G	530.1	770.8	215	58.41	119.7	111	89

achieve the highest sum of efficiency scores for each selected DMU ($i = v$). This constraint applies weights generated for each separate DMU analysis to all other DMUs inputs and outputs for relative efficiency comparison, just as is done in traditional DEA. However, this constraint makes the problem non-linear since the input weights are multiplied against the input changes.

In (4), we force the sum of the weighted and adjusted (re-allocated) inputs to be equal to one for each DMU. Doing so ensures that we will have efficiency scores for each DMU less than or equal to one. Again, this constraint is non-linear. In (5), we force each remaining input (after adjustment) for each DMU to be greater than or equal to zero. Negative resources are not feasible. The constraints in (6) require that any input adjustments sum to zero. We cannot grow resources for reallocation. Finally, the last set of constraints depicted in (7) is the bounds for the decision variables.

One might also include health care management constraints regarding the maximum movement of system resources to increase flexibility and reflect management input into the system. Doing so would simply require bounds on the appropriate δ, and these constraints would represent decision-maker input.

3. Results and discussion

Upon formulating and solving the resource allocation-based optimization model presented above, the MAOM solution provides the decision-maker recommendations regarding staffing of providers and allocation of funding such that all facilities achieve at least the efficiency associated with the r constraint. With this model formulation, there is a method for providing decision-support regarding the automatic adjustment of all system inputs.

Before investigating the use of MAOM on the Military Health System, we validated its performance on a simple textbook problem related to healthcare systems (see Anderson *et al.*, 2012, p. 248). In this problem, seven different hospitals were initially evaluated using a constant returns-to-scale (CRS) form of DEA (Cooper *et al.*, 2007). FTEs, supply expenses, and available beds were inputs into the model, while patient days by age category, nurses trained, and interns were outputs. Table 1 provides the textbook example data.

We first solved this problem using a DEA formulation to replicate the textbook solution, and in the initial model, all hospitals were efficient except for Hospital D, which was 90.73% efficient. An analysis of reduced costs associated with the optimization run for Hospital D suggested reduction in FTEs of 12.16, expenses by $184.63K, or the number of interns by 7.67. The reference set (where duals are non-zero) for Hospital D includes Hospitals A, B, and E.

Typical sensitivity analysis would suggest a reduction in resources to Hospital D, but in the case of fixed inputs across a health system, this solution is not feasible. This leads us to using the MAOM formulation, setting the minimum efficiency for any facility to at least .90 and side constraints to prevent the reallocation of more than 25% of input resources. Running the MAOM results in all hospitals becoming 100% efficient. The input adjustment matrix (Table 2) shows the recommended adjustments. To validate these results, we re-ran the new inputs and outputs through CRS DEA and confirmed that efficiencies were now all equal to one.

The result of the MAOM formulation in this textbook example recommended only changing the available bed days for the facilities (adding or removing beds or the associated supporting resources). The solution set is only one of many available, and several solution sets might be enumerated to

Table 2. Results from MAOM on textbook healthcare example

Hospital	FTEs	Supply Expenses	Available Bed Days
A	310.10	134.60	117.171
B	278.50	114.30	108.143
C	165.60	131.30	64.936
D	250.00	316.00	86.563
E	206.40	151.20	103.060
F	384.00	217.00	153.702
G	530.10	770.80	219.946

Table 3. Description of data sources from the military health system

Variable Name	Type	Description of Variables	Data Source
ENROLL	Input	**Population Measure:** enrollment population supported (in 1000s) in 2003. This input is non-discretionary.	M2
FTE	Input	**Worker Measure:** number of assigned full time equivalents (in 100s) in 2003.	MEPRS
COST	Input	**Cost Measure:** expenditures (in 1000s) less graduate medical education (training) and readiness costs, inflated in two parts to 2003 dollars.	MEPRS
RWP	Output	**Inpatient Workload Measure:** aggregated MTF relative weighted product (in 1000s) in 2003.	MEPRS
RVU	Output	**Outpatient Workload Measure:** aggregated MTF relative value unit (in 1000s) in 2003.	MEPRS
PREV	Output	**Quality Measure:** preventive care composite score found in survey scaled between [0, 100] in 2003.	HCSDB
SAT	Output	**Satisfaction Measure:** composite score (total score) found in survey scaled between [0, 100] in 2003.	HCSDB
ACCESS	Output	**Access Measure:** ease of access (getting needed care metric) composite score found in the survey scaled between [0, 100] in 2003.	HCSDB

Notes: M2 = MHS Management Analysis and Reporting Tool, a MHS data querying tool.
MEPRS = Medical Expense and Performance Reporting System, the accounting system for the MHS.
HCSDB = Health Care Survey of DoD Beneficiaries, developed by the Tricare Management Activity.

provide decision-support. Before discussing this further, we run the MAOM using real-world data from the MHS.

3.1. *Case study of the military health system*

We use the MAOM to solve a real-world example involving 16 U.S. Army hospitals in the MHS with health system data from 2003. The specific system inputs and outputs were deemed important to MHS decision makers in evaluating technical efficiency, which were validated from the previous literature. The data are from 2003 (as to be non-sensitive in nature), and the hospitals were chosen from 24 facilities because they are largely homogenous. Table 3 describes the set of system input and output variables selected for analyzing MHS performance.

The MHS inputs that could be manipulated included the funding stream (COST) and the FTE, but ENROLL is a non-discretionary input that cannot be re-allocated. The outputs of interest included RWP, RVU, PREV, SAT, and ACCESS. The data are shown in Table 4, where H1 through H16 represent the 16 U.S. Army hospitals considered in this case study.

As a means of comparing optimization models, we first ran a variable returns-to-scale (VRS) DEA analysis (Cooper *et al*., 2007) of these 16 treatment facilities, as such an analysis reasonably assumes that the production frontier is not necessarily linear. Assuming that ENROLL is a non-discretionary input, facilities with inefficiency scores less than 1.0 included: H1 (.851), H2 (.928), H5 (.948), H7 (.779), H8 (.951), H9 (.850), H11 (.998), H13 (.959), H14 (.842), and H16 (.974).

Because non-linear programming (NLP) solvers are likely to generate different solution sets and since local solutions are likely for some problems, we used multiple solvers and compared solution sets. Using the General Algebraic Modeling System (GAMS Development Corps, 2013) as the modeling language and the CONOPT (Drud, 1992) and MINOS (Murtagh and Saunders, 1983) NLP solvers, we ran the MHS data in the MAOM optimization model, which resulted in all treatment facilities achieving efficiency scores of 1.0 by re-allocating COST and FTE input resources as shown in Table 5 (CONOPT) and in Table 6 (MINOS). Both NLP model solvers executed this analysis nearly instantaneously. What is interesting about the CONOPT results is that the changes, while significant, are not so severe as to require side constraints in the MAOM model formulation. The MINOS solver, however, required two side constraints to prevent near elimination of FTEs for facility H12. This result shows the importance of binding the feasible region (set of feasible solutions) better, especially since multiple optimal solutions are possible if not likely. The side constraints added for the MINOS solver prevented more than 25% reductions or 25% increases in flexible system inputs. It is important to note that it is even possible that the resource allocated-based auto-optimization model might have recommended the elimination of FTEs or funding from a facility.

To illustrate what the results mean to decision makers, we turn to Table 6, the MINOS solution set. For H1 (Hospital 1), the original funding for the facility was \$56.66K. The final cost is \$56.66K. No change is recommended. But for Hospital 1, we see that the original number of FTEs was 713, and the recommended FTEs is 891. The results would suggest increasing the number of FTEs by 178. Also note that the correlation between FTE and COST reduced from 0.96 to 0.83 upon re-allocating resources.

Table 4. Data from the military health system (U.S. Army hospitals)

Hospital	ENROLL	FTE	COST	RWP	RVU	PREV	ACCESS	SAT
H1	14.81	7.13	56.66	7.05	112.21	83.28	70.55	73.19
H2	23.09	9.86	72.67	6.51	182.38	83.40	66.24	71.55
H3	68.40	17.66	163.99	21.74	372.06	78.89	57.29	63.02
H4	80.62	17.20	169.14	14.14	476.48	89.14	67.39	73.63
H5	49.84	15.25	125.44	16.87	314.98	85.65	65.72	72.02
H6	38.13	13.04	130.23	10.41	229.08	84.82	65.61	69.87
H7	32.87	8.68	67.25	10.74	187.00	79.70	67.86	70.83
H8	12.74	6.34	53.16	7.07	85.10	84.60	67.49	73.67
H9	23.95	11.73	95.60	14.31	253.72	83.15	70.59	74.81
H10	14.93	6.42	52.37	0.96	76.53	89.44	65.40	69.85
H11	47.87	16.91	129.16	21.93	339.66	85.73	69.30	74.35
H12	31.50	8.81	71.98	3.01	153.56	82.32	60.92	69.81
H13	22.99	11.13	99.60	6.71	252.20	85.63	74.52	80.99
H14	31.39	12.73	92.53	14.87	298.59	83.97	70.48	75.62
H15	10.70	6.22	38.08	3.03	60.06	80.83	64.76	72.84
H16	63.40	14.71	114.29	14.86	327.31	80.24	62.89	68.53

Again, we note that multiple optimal solutions are likely to be available for many non-linear optimization problems. Investigating these multiple optimal solutions is something that is important in order to provide quality decision-support for efficient resource allocation. To investigate the optimal solution set, we next ran the MAOM using a multi-start genetic algorithm (GA) solver, MSNLP (Smith and Lasdon, 1992), and the side constraints specified for the MINOS runs. We allowed the GA to run for 1000 seconds and 1000 iterations. The GA solver found the first optimal solution in 200 iterations (during pre-processing). Afterwards, propagation continued for the full 1000 iterations. The final offspring with the best merit function resulted in the optimal solution provided by Table 7. One of the major advantages to the multi-start GA modeling approach, however, is that it produces a family of possible solutions for decision makers to consider in re-allocating health system input resources across multiple competing objectives (such as workload, prevention, satisfaction, and access). We will discuss this later.

From Table 5 and Table 6, respectively, we notice that the CONOPT solver recommended minor changes in funding, while the MINOS solver recommended no changes (a constant). On the other hand, Table 7 shows that the MSNLP solver produced more significant funding shifts. Further, we noticed that the directionality change of 11 of the 16 hospitals was identical for FTEs. Table 8 provides a congruency analysis based on recommended adjustments (resource

Table 5. MHS performance results from MAOM using the CONOPT solver

Hospital	ORIGINAL COST	NEW COST	ORIGINAL FTE	NEW FTE
H1	56.66	53.41	7.13	7.94
H2	72.67	72.63	9.86	9.64
H3	163.99	163.98	17.66	16.35
H4	169.14	174.81	17.20	17.47
H5	125.44	125.43	15.25	13.33
H6	130.23	130.21	13.04	10.28
H7	67.25	64.98	8.68	10.42
H8	53.16	53.16	6.34	6.16
H9	95.60	95.59	11.73	11.62
H10	52.37	52.38	6.42	6.30
H11	129.16	129.15	16.91	17.00
H12	71.98	71.92	8.81	7.56
H13	99.60	99.61	11.13	10.55
H14	92.53	92.57	12.73	19.33
H15	38.08	38.10	6.22	5.39
H16	114.29	114.25	14.71	14.48

Table 6. MHS performance results from MAOM using the MINOS solver

Hospital	ORIGINAL COST	NEW COST	ORIGINAL FTE	NEW FTE
H1	56.66	56.66	7.13	8.912
H2	72.67	72.67	9.86	7.573
H3	163.99	163.99	17.66	17.66
H4	169.14	169.14	17.20	17.20
H5	125.44	125.44	15.25	13.848
H6	130.23	130.23	13.04	9.78
H7	67.25	67.25	8.68	10.850
H8	53.16	53.16	6.34	7.925
H9	95.60	95.60	11.73	11.730
H10	52.37	52.37	6.42	6.420
H11	129.16	129.16	16.91	18.814
H12	71.98	71.98	8.81	6.607
H13	99.60	99.60	11.13	11.13
H14	92.53	92.53	12.73	15.912
H15	38.08	38.08	6.22	6.22
H16	114.29	114.29	14.71	13.238

Table 7. MHS performance results from MAOM using the MSNLP solver

Hospital	ORIGINAL COST	NEW COST	ORIGINAL FTE	NEW FTE
H1	56.66	42.509	7.13	8.912
H2	72.67	76.519	9.86	9.027
H3	163.99	140.318	17.66	18.614
H4	169.14	211.425	17.20	14.424
H5	125.44	121.896	15.25	15.496
H6	130.23	97.672	13.04	10.794
H7	67.25	75.117	8.68	10.792
H8	53.16	39.87	6.34	7.925
H9	95.60	119.5	11.73	11.609
H10	52.37	48.317	6.42	4.815
H11	129.16	96.87	16.91	21.137
H12	71.98	75.358	8.81	6.607
H13	99.60	117.944	11.13	8.428
H14	92.53	97.419	12.73	15.912
H15	38.08	28.56	6.22	6.221
H16	114.29	142.857	14.71	13.106

re-allocations) by the three different NLP modeling solvers. Positive congruence indicates that all solvers recommended FTE increases, while negative congruence indicates that all solvers recommended decreases. "Semi-Negative" indicates that all solvers recommended either reductions or no increases. Different recommendations (both positive or negative) are annotated as "Mixed."

The results from the MAOM imply that a set of possible optimal solutions should be presented to health system decision makers considering the re-allocation of system inputs, and the use of multi-start evolutionary algorithms appear to be a reasonable method for doing so. In fact, quick congruence may be desirable; however, if any side constraints are missing, the results may be less than optimal from a decision makers' perspective. Therefore, we underscore the value of additional constraints in optimization analyses which are likely to produce multiple solutions. We also emphasize the value of investigating a family of optimal feasible solutions that maximize the efficiency of the overall system, as a single decision set may not provide sufficient flexibility for decision makers.

Table 8. Congruency analysis of solvers for FTEs

Hospital	MINOS	CONOPT	MSNLP	CONGRUENCE
H1	0.81	1.782	1.782	Positive
H2	−0.22	−2.287	−0.833	Negative
H3	−1.31	0	0.954	Mixed
H4	0.27	0	−2.776	Mixed
H5	−1.92	−1.402	0.246	Mixed
H6	−2.76	−3.26	−2.246	Negative
H7	1.74	2.17	2.112	Positive
H8	−0.18	1.585	1.585	Mixed
H9	−0.11	0	−0.121	Semi-Negative
H10	−0.12	0	−1.605	Semi-Negative
H11	0.09	1.904	4.227	Positive
H12	−1.25	−2.203	−2.203	Negative
H13	−0.58	0	−2.702	Semi-Negative
H14	6.6	3.182	3.182	Positive
H15	−0.83	0	0.001	Mixed
H16	−0.23	−1.472	−1.604	Negative

4. Concluding remarks

The necessity to efficiently balance and re-allocate resources among hospitals is paramount, especially as health systems experience increasing demand and cost for health services. In this paper, we provided an original resource allocation-based optimization model as an alternative to traditional DEA and MCMP approaches that adjusts resources (system inputs) automatically. We applied the MAOM optimization model to a real-world data set involving U.S. Army hospitals in the MHS, which demonstrated how FTE and COST input variables could be efficiently re-allocated to maximize the MHS performance. Note that this resource allocation-based optimization model can analyze overall system performance with more (or less) system input and output variables as well as more (or less) less DMUs (military treatment facilities). Further, this optimization model should be employed as a decision-support tool for the automatic re-allocation of resources (system inputs) in order to optimize overall system efficiency (performance) where the system outputs are maintained. The automatic adjustment of input resources is advantageous as it can be extremely difficult for decision makers in the health system to assign appropriate weights in the model, which is typical of the traditional DEA and MOOP methods.

Moreover, the utility for this type of decision-support model to be employed in support of resource allocations for large, centrally funded health systems is self-evident. As both cost and demand for health services continue to increase, the need for efficient resource re-allocation models based on competing objectives (system outputs) will become increasingly more important. Resource allocation-based optimization models similar to the MAOM proffered here will aid decision makers' efforts.

In conducting this case study and analysis of the MHS, we found utility in the use of multi-start evolutionary algorithms that store multiple optimal solutions for consideration by decision makers. We also found that the addition of appropriate side constraints in the optimization model formulation could ameliorate deviations (automatic system input adjustments) of significant magnitude.

Future work will see the implementation of this resource allocation-based optimization model on the entire MHS (including all U.S. Army, Navy, and Air Force medical treatment facilities) with expanded system inputs and outputs from more recent years. Furthermore, we aim to integrate this optimization model with the U.S. Army Medical Command's Performance Based Adjustment Model (PBAM), a pay-for-performance financial incentive program used to re-distribute funds and modify treatment facility resources based on actual medical practices and outcomes (quality, workload, satisfaction, etc.) compared to mere baseline performance goals.

Acknowledgments

We would like to thank the reviewers, Dr. Paul Griffin, Dr. Terry Harrison and Dr. Mark Swofford for their helpful feedback in improving the paper.

Funding

This article is based upon work supported by the National Science Foundation under Grant No. DGE1255832.

Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation, the Pennsylvania State University, the Texas State University, or the United States Army.

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