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OPTIMIZATION OF PUBLIC SERVICE MODEL WITH LIMITED RESOURCES USING LINEAR PROGRAMMING

A M H PARDEDE[1], A FAUZI[2], Y MAULITA[3], R J SIMAMORA[4]
[1,2,3]STMIK Kaputama, Jl. Veteran No. 4A-9A, Binjai, Sumatera Utara, Indonesia
[4]Universitas Methodist Indonesia, Medan, Sumatera Utara, Indonesia
E mail: akimmhp@live.com

ABSTRACT

In daily life, people may require public services, which in this study refer to healthcare, security, protection, and emergency assistance involving threats to public safety. Public services are necessary in both routine and emergency situations where life-saving interventions must be delivered as quickly as possible, so the problem to be solved in this paper is how to provide appropriate and fast services to people who need services by utilizing limited resources. The goal is to provide timely services with limited resources from hospitals, police departments, fire departments, and the Regional Disaster Management Agency (RDMA/BPBD). When delivering public services, medical staff (*me*), police (*po*), firefighters (*fi*), and BPBD (*bn*) depart from their respective locations such as hospitals (*ime*), police stations (*ipo*), fire stations (*ifi*), and BPBD offices (*ibn*) to the victims' locations (*j*) to provide services. The model developed in this research addresses challenges by delivering intelligent services as early as possible, reducing fatalities caused by delays, minimizing costs, shortening service times, maximizing resource utilization, and achieving the maximum value from the model's objective function. The information obtained includes the type of solver used—either "B-and-B," "Global," or "Multi-start," depending on the specific solver employed. The objective value was 169.0000, with an objective bound of 169.0000, zero infeasibilities, zero extended solver steps, 20 total solver iterations, and an elapsed runtime of 0.19 seconds. The model is classified as MILP, consisting of 100 total variables, 128 total constraints, and 750 nonzero elements. The designed modeling results have successfully minimized travel costs, service costs, and other costs arising from inaccuracies in patient care delivery.
Keywords: *Emergency; Health; Model; Optimization; Service.*

1. INTRODUCTION

Public services are essential in both everyday situations and emergencies, where life-saving interventions must be provided promptly. In such cases, it is crucial to ensure coordination among service centers that need to collaborate effectively [1], [2]. To deliver more effective emergency response services, a smart approach is required [3], similar to the "Safe City" concept, which is designed for rapid emergency response [4]. Public services must be capable of addressing various scenarios, and this research focuses on emergencies requiring immediate public assistance, such as medical crises, traffic accidents, criminal incidents, and fires

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Integrating design thinking can optimize healthcare delivery and significantly enhance patient-centered care, especially in settings with limited resources [5], [6]. In the United States, specialized centers have been established to adopt design thinking principles to advance patient care [7], [8]. Numerous studies have indicated that design thinking fosters innovation within clinical and managerial contexts across various medical specialties [9]. Furthermore, design thinking facilitates the development of tailored solutions for low-resource environments. Compared to traditional methods, it has the potential to provide care that is usable, acceptable, and effective [10]. Recent research has reported the application of design thinking in a range of interdisciplinary innovation projects within fields such as pediatrics, psychiatry, radiology, gastroenterology, oncology, orthopedics, and surgery, as well as its utilization in hospital operations and healthcare management [8]. Moreover, design thinking has proven to be a catalyst by engaging patient-centered service providers and IT specialists in the development of solutions, thus enabling the creation of specific future scenarios and precise requirements [11].

The public service model has been modified by previous researchers by incorporating individualistic behavior to include decision-making [14], collision avoidance among public service providers [15], and cognitive abilities such as

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altruism and the emotional impact of victim behavior [16].

When resources at the service center are abundant, optimal service delivery can be achieved. However, even in such conditions, it is not guaranteed that operations will be efficient, as surplus resources could lead to unnecessary costs. Conversely, if demand exceeds the available resources, it may result in unmet service needs, causing long waiting queues. This issue becomes more critical if the demand involves emergency patients (priority patients), and must be carefully managed to prevent negative outcomes for both service providers and patients. Health service requests submitted by patients, which include details about the desired location and type of service, are received by servers connected to the internet. These requests are then scheduled by the hospital's server. Communication among resources within the server allows for efficient time allocation for each health service, ensuring that limited resources are utilized effectively to meet patient needs. The variables analyzed in this study include hospital resources, focusing on optimizing the early provision of healthcare services within resource constraints. The maximum objective function value reached was 75.00000 at the 28th iteration [17].

Travel costs need to be minimized, including expenses for transporting healthcare providers to patients, the cost of medical personnel delivering specific services, and the travel time from the service location to the patient. Other considerations include the time it takes for medical personnel to reach the patient before starting treatment, the earliest time the patient can receive care, and the latest acceptable time for the patient to receive the service [18].

A new paradigm is emerging to support applications across various fields, such as home automation, automotive systems, traffic management, mobile healthcare, elderly care, industrial automation, medical assistance, smart energy management, and smart grids, among others [19]. The research framework for public service management is outlined in several stages, including developing a queueing model and constructing a mathematical model based on the objective function. Initial assumptions are applied as resource constraints, followed by the creation of a decision model, integrating two or more models, and conducting simulations to test the proposed models [20]. A model can also be utilized to minimize travel costs, service delivery expenses, and other costs that arise due to inefficiencies, which are considered penalty costs for inadequate service provision to patients (1), and optimizing patient care in a hospital can be achieved through the application of linear integer programming [19].

The simulation of hospital queue resource optimization can be performed using the Simulink model in MATLAB. The simulation runs for 1,440 minutes, equivalent to 24 hours a day, yielding an average busy probability of 12% for service centers, while the average patient waiting time to receive services is 30 minutes [21]. The design and optimization of a public service model involve managing incidents or series of events that disrupt and pose risks to the community, arising from natural or non-natural causes, as well as issues like health emergencies, traffic accidents, criminal activities, and fires. The objective is to enhance public service delivery while working within the limitations of available resources [22].
Previous studies need further refinement by incorporating new and distinct elements. This can be achieved by expanding the focus on hospital resources to include additional resource variables, such as police services, fire departments, and the Regional Disaster Management Agency (RDMA/BPBD). These variables are used to optimize public service models under resource constraints through the application of linear programming [23].

The goal of this research is to optimize a Smart Public Service Model using Linear Programming to Reduce Mortality. This is based on the "Smart Health and Safe City" concept, which aims to provide timely services by making the best use of the limited resources available to hospitals, police, fire departments, and the Regional Disaster Management Agency (RDMA/BPBD) [12]. In this model, medical personnel (*me*), police officers (*po*), firefighters (*fi*), and BPBD teams (*bn*) depart from their respective locations (*ime/ipo/ifi/ibn*) to the affected location (*j*) to provide necessary public services. The model aims to deliver smart, timely services that reduce the mortality rate by addressing delays in emergency response [13].

The primary issue addressed in this research is how to provide Smart Public Services in response to sudden and unforeseen events. It is essential to determine the necessary actions to be taken by decision-makers to ensure that public services can be delivered efficiently. Additionally,

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this approach should aim to reduce costs by addressing resource shortages at each public service center.

The approach to problem-solving and the specific goals of this research are:

1. Developing and optimizing a Smart Public Service Model using Linear Programming for the community, addressing events or series of events that threaten and disrupt public life caused by natural and/or non-natural factors, as well as human factors. These include health disruptions, traffic accidents, criminal incidents, and fires.
2. Maximizing public service with the constraints of available service provider resources, minimizing response time to both urgent and non-urgent incidents, reducing the time it takes for service providers to reach the scene, and shortening the time required for victim evacuation.

This research can be used as an alternative approach to decision-making in public service delivery. The model developed aims to address the challenge of providing intelligent services as early as possible, which can help reduce the number of deaths due to delays in service, minimize costs, reduce service delivery time, maximize resource utilization, and achieve the highest possible value from the model's objective function.

The significant problem formulations in this study are:

1. How to Determine Efficient Resource Allocation?
2. What is the Most Appropriate Objective Function for Optimizing Public Services?
3. How to Formulate Constraints Based on Resource Capacity?
4. How Optimally Can Public Services Be Improved with a Linear Programming Approach?
5. How to Overcome Limitations in Data or Assumptions for Modeling?

As a hypothesis in this paper, the use of linear programming models in the allocation of limited resources in public services will optimize the efficiency and effectiveness of services, increase the number of service recipients, and ensure that the quality of services is maintained without exceeding the available budget and capacity limits.

2. METHODS AND MATERIAL

From 2018 to 2023, the research team has conducted various studies and publications that support the achievement of the next research objectives for 2024. These efforts aim to develop a more optimal model for delivering public services with limited resources. The research roadmap and the publication record of the researchers are as follows:

1. From 2018 to 2019; The focus was on designing a patient queue management framework for decision support systems in intelligent healthcare and developing a decision support system model for intelligent healthcare services; Developing an optimal model for delivering healthcare services with limited resources; Testing the model to minimize hospital service costs.
2. From 2020 to 2021, the focus was on creating a simulation of emergency patient queue management as a support system for smart healthcare.
3. From 2022 to 2023, the focus was on developing an initial model for smart public service optimization using linear programming.
4. The plan for 2024 to 2025 involves testing the model in real-time at public service agencies based on available resources and producing a final prototype.
5. The plan for 2026 to 2027 involves implementing policies and systems derived from the results of the Comprehensive System research.

The research flowchart employs the concept of problem formulation through to the output results, which culminates in the Optimization of Public Service Models with Limited Resources Using Linear Programming [24]. The general research flowchart is depicted in Figure 1.

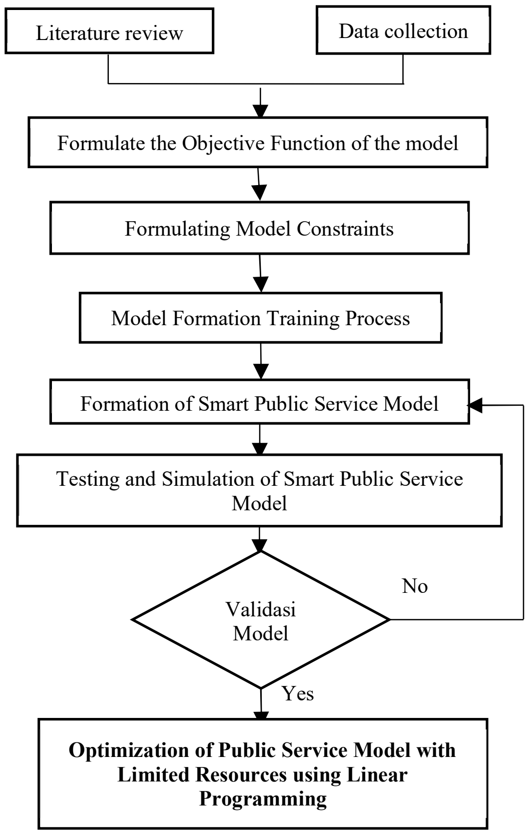

Figure 1: Research Flow Chart

The detailed explanation of the image above is provided in the following section:

1. Literature Review: Investigating the foundational theories and concepts of Smart Health, Safe Cities, evacuation planning, disaster traffic, operations research, mathematical modeling, healthcare management, linear programming, coordination, along with pertinent prior studies.
2. Data Collection: The data sources for this study include resource data from the medical health sector in hospitals and healthcare services, police resources, fire department resources, and resources from the Regional Disaster Management Agency.
3. Formulating the Objective Function of the Model: The objective function of the model being developed is to minimize service response time in accordance with the incident's impact on the victims.
4. Formulating a Constraint Model; Collecting resource constraint data.
5. Model Building; Creating an optimal model based on the concept of “Smart Health and Safe City”.
6. Model testing, simulation, and validation: Performing simulations and validations of the proposed model to address the identified problem.

3. RESULTS AND DISCUSSION

3.1 Data Collection

The data utilized in this study encompasses medical data from hospitals and health departments, police resources data, fire department resources data, and Regional Disaster Management Agency resources data. These numerical data, organized in matrix form, support the model development process and provide mathematical clarity to the model's objective functions. The data is derived from a set of matrices that represent the minimum amount of resources and costs incurred for each event, and then extracted from a series of function matrices. Detailed information is provided in the following table:

Table 1: This Function Indicates The Time Required For Medical Personnel To Travel From Point I To Point J To Save The Victim (Me)

me	*j = 1*	*j = 2*	*j = 3*	*j = 4*	*j = 5*
i = 1	7	30	17	7	5
i = 2	18	5	6	11	27
i = 3	15	19	9	21	15
i = 4	29	28	15	14	23
i = 5	22	14	23	6	5

The table presents the time required for medical personnel to travel to the victim's location to provide healthcare services, with the shortest assumed travel time being 5 minutes and the longest being 30 minutes. The table above explains the travel time for medical personnel (*me*) from me_{ij} (i = 1, j = 1) with a time of 7 minutes, travel time from me_{ij} (i = 1, j = 2) with a time of 30 minutes, travel time from me_{ij} (i = 1, j = 3) with a time of 17 minutes, and so on.

Table 2: This Function Represents The Time Required For The Police (Po) To Travel From Location I To Location J In Order To Assist In Rescuing The Victim

po	*j = 1*	*j = 2*	*j = 3*	*j = 4*	*j = 5*
i = 1	24	30	19	22	6
i = 2	21	18	14	20	22
i = 3	24	24	13	24	6
i = 4	26	17	28	30	11
i = 5	25	10	21	17	9

The table presents the time required for police units to travel to the victim's location to provide medical assistance, assuming the shortest travel time is 5 minutes and the longest is 30 minutes. The table above outlines the travel time for police units (*po*) from po_{ij} (i = 1, j = 1) with a time of 24 minutes, the travel time for medical personnel from po_{ij} (i = 1, j = 2) with a time of 30 minutes, the travel time for medical personnel from po_{ij} (i = 1, j = 3) with a time of 19 minutes, and so on.

Table 3: This Function Shows The Time Required For The Fire Brigade (Fi) To Travel From Location I To Location J To Assist In Rescuing The Victim.

fi	*j = 1*	*j = 2*	*j = 3*	*j = 4*	*j = 5*
i = 1	19	9	12	21	22
i = 2	7	6	14	27	10
i = 3	10	16	17	14	26
i = 4	18	15	30	24	13
i = 5	21	7	12	13	27

The table above details the travel time for the fire brigade (*fi*) from fi_{ij} (i = 1, j = 1) with a time of 19 minutes, the travel time for medical officers from fi_{ij} (i = 1, j = 2) with a time of 9 minutes, and the travel time for medical officers from fi_{ij} (i = 1, j = 3) with a time of 12 minutes, among others.

Table 3: This Function Shows The Time Required For The Fire Brigade (Fi) To Travel From Location I To Location J To Assist In Rescuing The Victim.

bn	*j = 1*	*j = 2*	*j = 3*	*j = 4*	*j = 5*
i = 1	20	20	22	22	10
i = 2	12	26	5	25	19
i = 3	20	25	30	15	26
i = 4	17	5	10	6	28
i = 5	15	16	29	5	14

The table above presents the travel times for the National BPBD (*bn*) from the location bn_{ij} (i = 1, j = 1), which takes 20 minutes, as well as the travel time for medical officers from bnij (i = 1, j = 2), also taking 20 minutes. Additionally, the travel time for medical officers from bn_{ij} (i = 1, j = 3) is 22 minutes, and so forth.

3.2 Formulating the Objective Function

The objective function of the developed model is to minimize the travel time from the public agency's location to the victim's site, reduce service time for the victims, and ensure that the delivery of services is appropriate for the specific incident concerning the victim. Below is one approach to formulating the optimization model [1]:

$$\begin{aligned} Minimum\ Z = & \sum_{i \in N} \sum_{j \in N} \alpha_{ij} \sum x_{ij}^{me} \\ & + \sum_{i \in N} \sum_{j \in N} \alpha_{ij} \sum x_{ij}^{po} \\ & + \sum_{i \in N} \sum_{j \in N} \alpha_{ij} \sum x_{ij}^{fi} \\ & + \sum_{i \in N} \sum_{j \in N} \alpha_{ij} \sum x_{ij}^{bn} \quad (1) \end{aligned}$$

Equation (1) outlines the objective function of the constructed model, which aims to minimize the travel time from the public agency's location to the victim's site, reduce service time for victims, and ensure the feasibility of delivering services appropriate to the incident. Specifically, it represents the travel time for medical personnel (*me*) from origin i to destination j in order to provide assistance in victim rescue, the travel time for police officers (*op*) from origin i to destination j for the same purpose, the travel time for the fire brigade (*fi*) from origin i to destination *j* to assist in victim rescue, and the travel time for the National BPBD (*bn*) from origin *i* to destination *j* for victim assistance.

3.3 Formulating a Constraint Model

The data collection on resource limitations serves as a key support in the implementation of this research. These limitations include the constraints on the number of medical personnel available to serve, the constraints on the number of police officers available to assist, the constraints on the number of firefighters available to respond, and the constraints on the number of BPBD personnel available to provide services. The following table presents this data.

Table 4: Medical Resources

Medical Personnel	Number
General Doctor	33
Surgical Specialist	2
Internal Medicine Specialist	4
Pediatrician Specialist	6
Obstetrician and Gynecologist Specialist	2
Clinical Pathology Specialist	3
Ear Nose Throat Specialist	4
Eye Specialist	2
Pulmonologist	3
Anesthesiologist	2
Neurologist	3
Dermatologist and Venereologist	1
Orthopedic Surgeon	2
Psychiatrist	1
Radiologist	1

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Pathologist	3
Forensic Specialist	1
Heartologist	2
Neurosurgeon	0
Dentist	6
Medical Rehabilitation Specialist	2
Plastic Surgeon	1
Total number	**84**

Table 5: Nursing Resources

Nursing Pramedic	Number
S-2 Nursing	2
S-1 Nursing	105
Nursing Academy	80
Health Nursing School	8
Midwife D4	9
Nurse Midwife D3	73
Midwife D1	1
Total number	**278**

Establishing the boundaries of the model to be developed and determining the problem parameters or initial values are the first steps in formulating the model's constraints. The restrictions or limitations that must be satisfied for the model to function effectively are outlined as follows:

1. Ensure that each victim is served only once by appropriate resources: Each victim j can only be served by one type of public service (medical, police, fire brigade, or BPBD), depending on the specific needs of the victim.
   Constraint:
   $$\sum_{i\in N}\sum_{j\in N} x_{ij}^{mepofibn} \leq |1| \;\; \forall_i \in N \;\; \backslash\{0\} \qquad (2)$$
   Where Xme^{ij}, Xpo^{ij}, Xfi^{ij}, and Xbn^{ij} are binary variables indicating whether the respective service (medical, police, fire brigade, or BPBD) is provided from resource i to victim j.These variables take the value of 1 if the service is assigned, and 0 otherwise.
2. Providing services to victims can be carried out with some or all public services: Services may be provided by one or more public service types, depending on the victim's needs. This constraint will be combined with the first constraint.
   Constraint: Same as the first constraint.
   This ensures that each victim is assigned the appropriate combination of public services (medical, police, fire brigade, or BPBD) based on their needs.
3. Each victim receives service only once: Each victim is served only once, ensuring that no service is repeated or provided partially.
   Constraint: Same as the first constraint.
4. Public services depart immediately upon completion: Once the service is rendered to the affected individual at location j, public resources cannot provide additional services to the same individual.
   Constraint:
   The departure time from victim j is equal to the arrival time at victim j plus the service time at victim j. This will be implemented in the time variables for each affected individual and the services provided.
5. Elimination of Sub-Tours: Prevent the formation of sub-tours or loops within the service routes.
   Constraint:
   $$U_i - U_j + N \times X_{ij} \leq N - 1 \qquad (3)$$
   $$w_j = maks\left(me_j - po_j - fi_j - bn_j\right) \forall_j \in N\{0, i\} \qquad (4)$$
   Where U_i and U_j are decision variables ensuring that the service does not return to the origin within the same journey, and N represents the total number of affected individuals.
6. Limitations on the Number of Medical, Police, Fire, and Disaster Management Services: Each type of public service is subject to restrictions on the availability of resources at each location.
   Constraint:
   $$\sum_{i\in N} x_{ij}^{me} \leq C_i^{me} \qquad (5)$$
   $$\sum_{i\in N}\sum_{j\in N} x_{ij}^{mepofibn} =< 4 \; \forall_i \in N \;\; \backslash\{0\} \; (6)$$
   Where C*mei* represents the maximum capacity of medical services from location *i*, and similar constraints apply to police, fire, and disaster management services.
7. Victim Waiting Time: The waiting time for victims encompasses both the travel time and the duration required for public services to reach the victim's location.
   Constraint:
   $$\text{Waiting time at victim j} = \text{Arrival time at victim j} - \text{Request time at victim j} \qquad (7)$$
8. Determine Officer Arrival Time: The arrival time of the service is calculated based on the total duration required for travel from the origin location to the victim's location, plus the time needed to complete the service.

Constraint:
Arrival time at victim j = start time at origin i + travel time from i to j (8)

9. Sanctions Based on Arrival Time: Penalties are imposed if services arrive either too late or too early, with larger delays resulting in greater penalties.
Constraint:
Penalty at victim j=α× (Actual arrival time at victim j−Designated arrival time at victim j) (9)
Where α is the penalty coefficient that depends on the extent of the delay.
10. Prerequisites for Public Services: Each public service must meet specific criteria to provide assistance.
Constraint:
$X_{ij}=1,$
Service type requirements at victim j are met (10)
This is a logic-based constraint that can be adjusted according to the type of service provided.
11. Time Limitations: There are time restrictions for each service, requiring public services to respond promptly to victims with higher priority.
Constraint:
Service time at victim j≤Tmax

$$\sum_{i\in N}\sum_{j\in N} x_{ij}^{mepofibn} = 1 \ \forall_i \in N \ \backslash\{0\} \qquad (11)$$

12. Binary Decision Variable Range: The decision variables are binary, taking values of either 0 or 1.
Constraint:
$X_{ij}\in\{0,1\}$ (12)
These constraints will be utilized to calculate the total time required for services to reach the victims.

3.4 Model Building

The primary issue described in optimizing healthcare services under the "Smart Health and Safe City" concept is how to provide services as early as possible given the limited resources of hospitals, police, fire departments, and the Regional Disaster Management Agency. In this context, public services medical (*me*), police (*po*), fire (*fi*), and BPBD (*bn*) depart from their respective locations (*ime/ipo/ifi/ibn*) to provide assistance at location *j*. The model aims to solve this issue through Optimization of a Smart Public Service Model with Limited Resources Using Linear Programming, with the goal of maximizing intelligent public service delivery while minimizing time or costs incurred.

The objectives of the modeling phase are to maximize smart healthcare services and minimize costs by addressing the following:

1. The time required for medical services (*me*) to reach the affected location i.
2. The time required for police (*po*) to reach the affected location i.
3. The time required for fire services (*fi*) to reach the affected location i.
4. The time required for BPBD (*bn*) to reach the affected location i.

3.5 Model testing simulation and validation

The results from testing the proposed model to address the research problem focus on minimizing travel costs, service costs, and penalties for delays, ensuring that all patient requests are addressed. The proposed model is presented as an optimization model.

The objective function of the model aims to minimize the travel time from the public agency's location to the victim, minimize the service time for victims, and ensure that services are delivered appropriately according to the incident. Below is one approach to express the optimization model [1]:

$$\begin{aligned} Minimum\ Z &= \sum_{i\in N}\sum_{j\in N}\alpha_{ij}\sum x_{ij}^{me} + \sum_{i\in N}\sum_{j\in N}\alpha_{ij}\sum x_{ij}^{po} \\ &+ \sum_{i\in N}\sum_{j\in N}\alpha_{ij}\sum x_{ij}^{fi} \\ &+ \sum_{i\in N}\sum_{j\in N}\alpha_{ij}\sum x_{ij}^{bn} \qquad Eq.(1) \end{aligned}$$

The following presents the mathematical notations or symbols used in the model:

Set

i = is a symbol to indicate a group of places where victim services are carried out.
j = is a symbol to indicate a set of destinations for services to the next victim
$i,j \in N = (0,1,\dots,n)$
o = Symbol used as service center
me = Symbol used as a set of medical staff;
$me \in ME = (1,\dots,n)$
po = Symbol used as a set of Police staff
$po \in PO = (1,\dots,n)$
fi = Symbol used as a set of fire brigade staff;
$fi \in FI = (1,\dots,n)$
bn = Symbol used as a set of BPBD staff;
$bn \in BN = (1,\dots,n)$
k = Symbol used as the type of service;
$k \in k = (1,\dots,n)$

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Parameter

me_{ij} = medical time used to travel from place *i to place j*

po_{ij} = police time used to travel from place i to place j

fi_{ij} = fire brigade time used to travel from place i to place j

bn_{ij} = BPBD time used to travel from place i to place j

α_{ij} = time used to travel from place i to place j to provide assistance to save the victim

τ_j= Time of service to *to save the victim j*

W = waiting period before beginning care for the victim while medical personnel are on their way to the scene

a_i = The first time Victim i received services i receives service

b_i = Before the patient i receives care, at the latest

S_{ih} = The time it takes for medical professionals to get to a victim's location when they require resources; $S_i = a_i$

D_i = The amount of time needed for medical staff to depart from the victim's location after they have finished providing care. So there is a time lag;

$S_i \in [a_i, b_i]$, $D_i = maks\{w_i + \tau_i, a_i + \tau_i\}$

y_{khj} = If the kind of service k can be given by medical personnel h in place of patient j who needs it, the parameter is worth 1, and if not, it is worth 0.

z_{ij} = The parameter is worth 1 if the place of patient j has priority than where the patient i, is worth 0 if not.

Decision Variable

The decision variable in this model is a binary variable.

x_{ij}^{hk} = 1, if medical personnel h provide the kind of care k at the patient's location, and = 0 otherwise.

3.6 Mathematical Modeling Calculations

The Linear Interactive and Discrete Optimizer (LINDO) modeling application was utilized to conduct mathematical modeling and calculations to solve this problem. The model aims to minimize the time victims spend receiving services, including medical care, police assistance, firefighting, and disaster management. By reducing the time spent in service, the model optimizes resource allocation and enhances response efficiency.

Min 7 ME11 + 30 ME12 + 17 ME13 + 7 ME14 + 5 ME15
+ 18 ME21 + 5 ME22 + 6 ME23 + 11 ME24 + 27 ME25
+ 15 ME31 + 19 ME32 + 9 ME33 + 21 ME34 + 15 ME35
+ 29 ME41 + 28 ME42 + 15 ME43 + 14 ME44 + 23 ME45
+ 22 ME51 + 14 ME52 + 23 ME53 + 6 ME54 + 5 ME55

+ 24 PO11 + 30 PO12 + 19 PO13 + 22 PO14 + 6 PO15
+ 21 PO21 + 18 PO22 + 14 PO23 + 20 PO24 + 22 PO25
+ 24 PO31 + 24 PO32 + 13 PO33 + 24 PO34 + 6 PO35
+ 26 PO41 + 17 PO42 + 28 PO43 + 30 PO44 + 11 PO45
+ 25 PO51 + 10 PO52 + 21 PO53 + 17 PO54 + 9 PO55

+ 19 FI11 + 9 FI12 + 12 FI13 + 21 FI14 + 22 FI15
+ 7 FI21 + 6 FI22 + 14 FI23 + 27 FI24 + 10 FI25
+ 10 FI31 + 16 FI32 + 17 FI33 + 14 FI34 + 26 FI35
+ 18 FI41 + 15 FI42 + 30 FI43 + 24 FI44 + 13 FI45
+ 21 FI51 + 7 FI52 + 12 FI53 + 13 FI54 + 27 FI55

+ 20 BN11 + 20 BN12 + 22 BN13 + 22 BN14 + 10 BN15
+ 12 BN21 + 26 BN22 + 5 BN23 + 25 BN24 + 19 BN25
+ 20 BN31 + 25 BN32 + 30 BN33 + 15 BN34 + 26 BN35
+ 17 BN41 + 5 BN42 + 10 BN43 + 6 BN44 + 28 BN45
+ 15 BN51 + 16 BN52 + 29 BN53 + 5 BN54 + 14 BN55

The Solver type used was either "B-and-B," "Global," or "Multi-start," depending on the specific solver employed for the optimization task. The model produced the following results: Objective value 169.0000, Objective bound: 169.0000, Infeasibilities: 0.000000, Extended solver steps: 0, Total solver iterations: 20, Elapsed runtime seconds: 0.19, Model Class: MILP, Total variables: 100, Nonlinear variables: 0, Integer variables: 1, Total constraints: 128, Nonlinear constraints: 0, Total nonzeros: 750, and Nonlinear nonzeros: 0. The table below presents the values of the optimal decision variables obtained from the model:

Table 6: Decision Variable

Variable	Value	Reduced Cost
ME11	0.000000	2.000.000
ME12	0.000000	2.500.000

ME13	0.000000	1.200.000
ME14	0.000000	2.000.000
ME15	1.000.000	0.000000
ME21	0.000000	1.300.000
ME22	1.000.000	0.000000
ME23	0.000000	1.000.000
ME24	0.000000	6.000.000
ME25	0.000000	2.200.000
ME31	0.000000	6.000.000
ME32	0.000000	1.000.000
ME33	1.000.000	0.000000
ME34	0.000000	1.200.000
ME35	0.000000	6.000.000
ME41	0.000000	1.500.000
ME42	0.000000	1.400.000
ME43	0.000000	1.000.000
ME44	1.000.000	0.000000
ME45	0.000000	9.000.000
ME51	0.000000	1.700.000
ME52	0.000000	9.000.000
ME53	0.000000	1.800.000
ME54	0.000000	1.000.000
ME55	1.000.000	0.000000
PO11	0.000000	1.800.000
PO12	0.000000	2.400.000
PO13	0.000000	1.300.000
PO14	0.000000	1.600.000
PO15	1.000.000	0.000000
PO21	0.000000	7.000.000
PO22	0.000000	4.000.000
PO23	1.000.000	0.000000
PO24	0.000000	6.000.000
PO25	0.000000	8.000.000
PO31	0.000000	1.800.000
PO32	0.000000	1.800.000
PO33	0.000000	7.000.000
PO34	0.000000	1.800.000
PO35	1.000.000	0.000000
PO41	0.000000	1.500.000
PO42	0.000000	6.000.000
PO43	0.000000	1.700.000
PO44	0.000000	1.900.000
PO45	1.000.000	0.000000
PO51	0.000000	1.600.000
PO52	0.000000	1.000.000
PO53	0.000000	1.200.000
PO54	0.000000	8.000.000
PO55	1.000.000	0.000000
FI11	0.000000	1.000.000
FI12	1.000.000	0.000000
FI13	0.000000	3.000.000

FI14	0.000000	1.200.000
FI15	0.000000	1.300.000
FI21	0.000000	1.000.000
FI22	1.000.000	0.000000
FI23	0.000000	8.000.000
FI24	0.000000	2.100.000
FI25	0.000000	4.000.000
FI31	1.000.000	0.000000
FI32	0.000000	6.000.000
FI33	0.000000	7.000.000
FI34	0.000000	4.000.000
FI35	0.000000	1.600.000
FI41	0.000000	5.000.000
FI42	0.000000	2.000.000
FI43	0.000000	1.700.000
FI44	0.000000	1.100.000
FI45	1.000.000	0.000000
FI51	0.000000	1.400.000
FI52	1.000.000	0.000000
FI53	0.000000	5.000.000
FI54	0.000000	6.000.000
FI55	0.000000	2.000.000
BN11	0.000000	1.000.000
BN12	0.000000	1.000.000
BN13	0.000000	1.200.000
BN14	0.000000	1.200.000
BN15	1.000.000	0.000000
BN21	0.000000	7.000.000
BN22	0.000000	2.100.000
BN23	1.000.000	0.000000
BN24	0.000000	2.000.000
BN25	0.000000	1.400.000
BN31	0.000000	5.000.000
BN32	0.000000	1.000.000
BN33	0.000000	1.500.000
BN34	1.000.000	0.000000
BN35	0.000000	1.100.000
BN41	0.000000	1.200.000
BN42	1.000.000	0.000000
BN43	0.000000	5.000.000
BN44	0.000000	1.000.000
BN45	0.000000	2.300.000
BN51	0.000000	1.000.000
BN52	0.000000	1.100.000
BN53	0.000000	2.400.000
BN54	1.000.000	0.000000
BN55	0.000000	9.000.000

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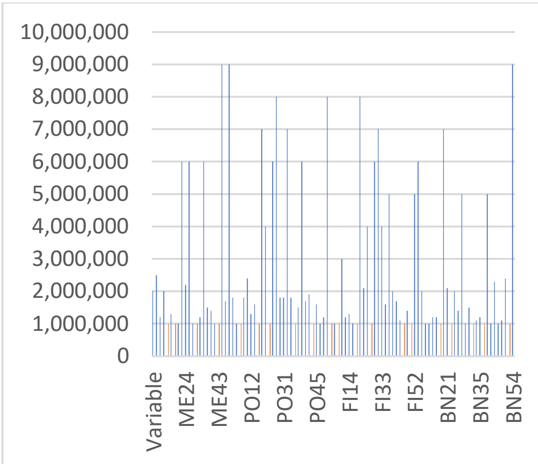

Figure 2: Optimal Decision Variable Values

Table 7: Slack Or Surplus

Row	Slack or Surplus	Dual Price
1	1.690.000	-1.000.000
2	4.000.000	0.000000
3	3.000.000	0.000000
4	4.000.000	0.000000
5	4.000.000	0.000000
6	1.000.000	0.000000
7	4.000.000	0.000000
8	2.000.000	0.000000
9	2.000.000	0.000000
10	4.000.000	0.000000
11	4.000.000	0.000000
12	3.000.000	0.000000
13	4.000.000	0.000000
14	3.000.000	0.000000
15	3.000.000	0.000000
16	3.000.000	0.000000
17	4.000.000	0.000000
18	3.000.000	0.000000
19	4.000.000	0.000000
20	3.000.000	0.000000
21	2.000.000	0.000000
22	4.000.000	0.000000
23	3.000.000	0.000000
24	4.000.000	0.000000
25	3.000.000	0.000000
26	2.000.000	0.000000
27	0.000000	-5.000.000
28	0.000000	-5.000.000
29	0.000000	-9.000.000
30	0.000000	-1.400.000
31	0.000000	-5.000.000
32	0.000000	-6.000.000
33	0.000000	-1.400.000
34	0.000000	-6.000.000
35	0.000000	-1.100.000
36	0.000000	-9.000.000
37	0.000000	-9.000.000
38	0.000000	-6.000.000
39	0.000000	-1.000.000
40	0.000000	-1.300.000
41	0.000000	-7.000.000
42	0.000000	-1.000.000
43	0.000000	-5.000.000
44	0.000000	-1.500.000
45	0.000000	-5.000.000
46	0.000000	-5.000.000
47	3.000.000	0.000000
48	3.000.000	0.000000
49	3.000.000	0.000000
50	3.000.000	0.000000
51	3.000.000	0.000000
52	3.000.000	0.000000
53	3.000.000	0.000000
54	3.000.000	0.000000
55	3.000.000	0.000000
56	3.000.000	0.000000
57	3.000.000	0.000000
58	3.000.000	0.000000
59	3.000.000	0.000000
60	3.000.000	0.000000
61	3.000.000	0.000000
62	3.000.000	0.000000
63	3.000.000	0.000000
64	3.000.000	0.000000
65	3.000.000	0.000000
66	3.000.000	0.000000
67	0.000000	0.000000
68	0.000000	0.000000
69	0.000000	0.000000
70	0.000000	0.000000
71	0.000000	0.000000
72	0.000000	0.000000
73	0.000000	0.000000
74	0.000000	0.000000
75	0.000000	0.000000
76	0.000000	0.000000
77	0.000000	0.000000
78	0.000000	0.000000
79	0.000000	0.000000
80	0.000000	0.000000
81	0.000000	0.000000
82	0.000000	0.000000
83	0.000000	0.000000
84	0.000000	0.000000
85	0.000000	0.000000

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86	0.000000	0.000000
87	7.000.000	0.000000
88	7.000.000	0.000000
89	7.000.000	0.000000
90	7.000.000	0.000000
91	7.000.000	0.000000
92	7.000.000	0.000000
93	7.000.000	0.000000
94	7.000.000	0.000000
95	7.000.000	0.000000
96	7.000.000	0.000000
97	7.000.000	0.000000
98	7.000.000	0.000000
99	7.000.000	0.000000
100	7.000.000	0.000000
101	7.000.000	0.000000
102	7.000.000	0.000000
103	7.000.000	0.000000
104	7.000.000	0.000000
105	7.000.000	0.000000
106	7.000.000	0.000000
107	4.000.000	0.000000
108	4.000.000	0.000000
109	4.000.000	0.000000
110	4.000.000	0.000000
111	4.000.000	0.000000
112	4.000.000	0.000000
113	4.000.000	0.000000
114	4.000.000	0.000000
115	4.000.000	0.000000
116	4.000.000	0.000000
117	4.000.000	0.000000
118	4.000.000	0.000000
119	4.000.000	0.000000
120	4.000.000	0.000000
121	4.000.000	0.000000
122	4.000.000	0.000000
123	4.000.000	0.000000
124	4.000.000	0.000000
125	4.000.000	0.000000
126	4.000.000	0.000000
127	2.500.000	0.000000
128	2.500.000	0.000000

Slack or surplus provides an indication of whether a constraint is active. If the slack or surplus is zero, the constraint is classified as active. Conversely, if the slack or surplus is non-zero, the constraint is deemed inactive. For instance, in row 27, the constraint is identified as active with a dual price of -5.00. This value signifies that increasing the right-hand side of the constraint by one unit will result in a decrease of the objective function by 5.00.

4. CONCLUSIONS

From the findings of this study, the following conclusions can be drawn:

1. The intelligent healthcare service optimization model serves to enhance the delivery of healthcare services based on the Smart Health concept. It focuses on providing high-quality care to patients as quickly as possible while reducing healthcare costs and addressing the issue of limited nursing staff resources through optimal resource utilization.
2. This model is designed to minimize travel expenses, service costs, and other costs that arise from inaccuracies in patient service delivery.
3. Active constraints with negative dual prices indicate that an increase of one unit in the right-hand side value of these constraints will lead to a decrease in the objective function value.
4. The information obtained indicates that the solver type is either "B-and-B," "Global," or "Multi-start," depending on the specific solver utilized. The objective value is 169.0000, with an objective bound of 169.0000, indicating no infeasibilities (0.000000). The extended solver steps are 0, with a total of 20 solver iterations and an elapsed runtime of 0.19 seconds. The model class is MILP, comprising a total of 100 variables (with 0 nonlinear variables and 1 integer variable), 128 constraints (with 0 nonlinear constraints), 750 total nonzeros, and 0 nonlinear nonzeros.

This study has provided a structured framework for optimizing public service delivery with constrained resources using linear programming. The primary argument centers around the concept that limited public resources such as budget, workforce, and infrastructure require meticulous allocation to maximize impact. By leveraging linear programming, this work demonstrates how public service organizations can make data-driven decisions to allocate these resources efficiently, ensuring that services reach a broader segment of the population without exceeding constraints.

Through mathematical modeling, we have shown that it is possible to optimize both the reach and quality of public services by focusing on a function objective, such as cost minimization or maximization of service access, and adhering to predefined constraints. The results support the notion that resource optimization models can significantly enhance service delivery outcomes while respecting the inherent limits in public service settings.

However, several questions arise that extend beyond the scope of this study. For instance:

1. Dynamic Changes in Demand and Resources: This work assumes a static model of demand and resource availability. How would fluctuations in demand or changes in resource allocations throughout the year affect the model's effectiveness?
2. Quantifying Social Impact: While this study focuses on maximizing the number of service recipients or minimizing costs, it does not directly quantify social impact, such as improved quality of life or social equity. How can the model incorporate these broader social outcomes into the optimization function?
3. Adaptation to Real-World Constraints: Linear programming assumes a high degree of data accuracy and stable conditions, which may not always hold in public service contexts. What methods could be used to adjust the model for real-world unpredictability, such as policy shifts, economic changes, or unforeseen crises?

5. SUGGESTIONS

The suggestions that can be given in this study are as follows:

1. The resulting model is expected to be combined with a measurement model of the priority level of patient requests.
2. The resulting model needs to be further developed by adding constraint variables and conducting simulations in various locations, so that it can maximize services at the service center.
3. For the sustainability of this research, it needs to be implemented in online and real-time applications, and it is recommended to combine resources from several hospitals so that services can be more optimal

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