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A smart city infrastructure implementation framework – insights from smart street lighting implementation optimization

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ABSTRACT

In recent years, the concept of smart cities and infrastructure has gained momentum as a solution to challenges such as population growth, resource management, and environmental sustainability. Rapid urbanization in many developing countries highlights the need for efficient infrastructure planning and management. This framework offers a structured approach for decision-making and resource allocation, enabling prioritization of investments to maximize limited resources while supporting development goals. The framework is tested through an analysis of the Smart Street Lighting Systems (SSLS) in Surabaya, Indonesia, addressing the city's intention to upgrade street lighting to reduce maintenance costs and energy consumption. Currently, the street lighting system faces issues including a high rate of broken or damaged lights and inefficiencies in handling complaints. However, limited funding and varied regional needs constrain any comprehensive upgrade. The proposed framework integrates the Analytical Hierarchy Process (AHP) to prioritize regions as weighting inputs, Mixed Integer Goal Programming (MIGP) to optimize the distribution of SSLS and conventional LED lighting across regions, and Cost-Benefit Analysis (CBA) to evaluate financial feasibility. Results recommend purchasing 11,915 new SSLS units with region-specific distributions, achieving a financially viable Benefit-Cost Ratio (BCR) of 2.059. These findings demonstrate practical implementation of smart city principles, balancing cost-efficiency, service performance, and stakeholder priorities. Policymakers can use this framework to maximize impact within budget constraints. This framework serves as a viable template for other regions and countries embarking on smart city infrastructure implementation.

1. Introduction

With the rapid growth of cities around the world, innovative solutions to address the pressing challenges such as population growth, resource management and environmental sustainability in urban centers are becoming increasingly pertinent. Urbanization is characterized by unprecedented population increases; by 2050, it is projected that over 66% of the global population will reside in urban areas [1]. In recent years, the concept of smart cities has gained significant traction globally. Smart city is defined as a technologically modern urban area that uses different types of electronic methods, sensors and equipment to collect data. Information gained from the data is used to manage resources and services efficiently which improves operations across the city. The adoption of Internet of Things (IoT) systems is examined for its potential to enhance urban management and promote efficient resource use, underscoring the importance of technological integration in city planning [2]. Smart cities are defined both in terms of the infrastructure which collects and stores data and information as well as the method in which the municipalities monitor, analyze, plan and govern the city using the collected information. Smart city infrastructure plays a pivotal role in urbanization shift, leveraging advanced technologies to enhance the efficiency, safety, and quality of urban life. Sustainable urban planning methodologies are increasingly being constructed to tackle these pressing challenges. Strategies that incorporate both environmental and social considerations are necessary to foster resilience amid rapid urban changes [3]. In response, sustainable urban planning methodologies are increasingly developed to confront these interconnected challenges.

Smart city infrastructure encompasses a broad array of interconnected systems. At the core of this infrastructure lies the integration of information and communication technologies, enabling data collection, analysis and accelerated decision making [4]–[7]. However, while the benefits of smart city infrastructure are undeniable, its implementation poses unique challenges for developing countries, which often face limited resources, inadequate infrastructure, and competing socioeconomic priorities [8]. Firstly, Wungo et al. discuss the integration of urban design management in smart city concepts, noting the importance of optimizing public resources to improve service delivery while reducing operational costs [9]. Nonetheless, this goal becomes exceptionally challenging in developing regions where limited financial and infrastructural resources hinder the effective implementation of smart technologies. Conversely, Sulistyaningsih et al. provide insight into Indonesia's efforts to implement smart urban governance, emphasizing the necessity for substantial technological development to facilitate online urban services and the existing gaps in capability that still require addressing [10]. In the context of developing countries, where urbanization is occurring at an unprecedented pace, the need for effective infrastructure planning and management is particularly acute [11], [12] Cities face infrastructure bottlenecks that can hinder development and quality of life. For instance, the increasing urban population necessitates effective water management, transportation, and energy solutions [13]. Smart technologies, encompassing the Internet of Things (IoT), data analytics, and advanced communication systems, present substantial opportunities for infrastructure optimization. Such technologies allow for real-time monitoring and management of urban services, enabling cities to become more adaptive and responsive to residents' needs [14], [15]. By leveraging smart technologies, cities can overcome infrastructure bottlenecks, improve service delivery, address damages and needs promptly and create more resilient and livable environments for their residents [16]–[18].

To address implementation challenges in developing countries, this study proposes an integrated framework for optimizing smart city infrastructure investments. This smart city infrastructure framework is designed as a holistic approach which enable stakeholders to prioritize investments, maximize the impact of limited resources, and ensure that smart city initiatives are aligned with broader development goals and objectives. Through a case study of the implementation of Smart Street Lighting Systems (SSLS) in Surabaya, Indonesia, this manuscript illustrates the practical application of the proposed framework in a real-world urban context in its development, demonstrating its effectiveness in guiding policy formulation and infrastructure planning decisions.

Smart street lighting, in particular, offers a compelling entry point for smart city initiatives in developing countries. Beyond its primary function of illumination, smart lighting systems can serve as a foundational platform for deploying a wide range of urban services, from traffic management to environmental monitoring [19]–[22]. However, realizing the full potential of smart street lighting requires careful consideration of local contexts, priorities, and constraints.

In Surabaya, the Surabaya Department of Transportation (SubDOT) divides street lighting management into regional sectors, adhering to Indonesian regulations. Smart Street Lighting Systems (SSLS) in Indonesia have a technical lifespan standard of 50,000 hours, while conventional LED

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streetlights typically operate for 11.5 hours per day. However, Surabaya's policy differs, with lighting starting at 17:30 to 05:30. Factoring in technical lifespan and daily usage, LED lamps last approximately 12 years. Unlike conventional LEDs, SSLS incorporates dimming features, such as operating at full brightness from 18:00 to 24:00 and at 50% brightness from 00:01 to 05:30. Damaged lights are repaired according to city regulations and policy.

Surabaya manages 99,209 public streetlights across seven regions through SubDOT, aiming for Key Performance Indicator (KPI) repair times of less than 24 hours. Surabaya has begun implementing the Smart Street Lighting System (SSLS) with 1,878 units in operation, supported by additional personnel in the effort to become a Smart City. In 2022, 95,694 incidents of damage were reported, handled upon public complaints. Repair times for Conventional LED and SSLS are 46.67 and 4.5 hours per incident, respectively. SSLS promises to streamline repairs and minimize losses by significantly reducing repair times compared to traditional methods. SSLS contributes to faster repair times across all SubDOT regions, helping the city meet its target of sub-24-hour repairs. However, SubDOT cannot replace all Conventional LED units with SSLS due to procurement budget limitations.

Cost-Benefit Analysis (CBA) is a method used to evaluate alternatives based on their benefits and costs, often employed in projects involving government intervention. One key indicator in CBA is the Benefit-Cost Ratio (BCR), where higher ratios signify more optimal solutions. CBA can be integrated with optimization techniques like Mixed Integer Goal Programming (MIGP) to find the best solutions, especially for multi-objective optimization problems where not all constraints can be met [23]. MIGP prioritizes preferences determined through Analytical Hierarchy Process (AHP) calculations, transforming them into goal constraints [24].

This research proposes a new decision-making framework by combining AHP and MIGP to determine the optimal proportions of Conventional LED and SSLS across Surabaya's regions. The approach aligns with repair time KPIs while ensuring a viable Benefit-Cost Ratio (BCR). The study offers practical insights into the differing benefits provided by Conventional LED and SSLS [25]–[27]. The integration of AHP with financial indicators like the Benefit-Cost Ratio (BCR) in decision-making frameworks has been explored in various contexts, though it remains a relatively underutilized area. It also complements previous research using AHP and MIGP by emphasizing financial indicators, particularly BCR, which were previously underexplored [28]–[30]. This study can help Surabaya reduce the potential for errors in implementing the smart city concept [31], [32].

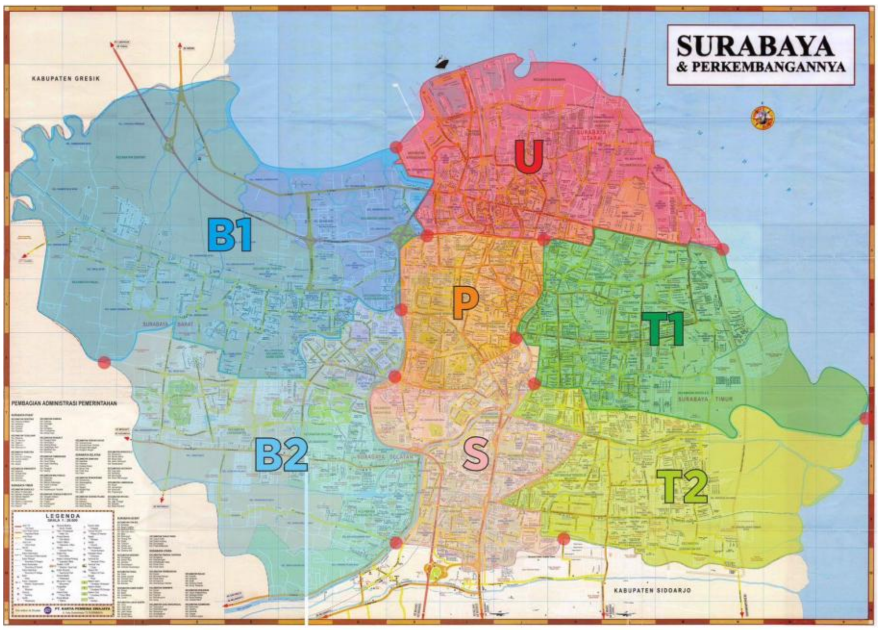

Fig. 1. SubDOT streetlight regions

Table 1. Existing conventional LED streetlights

Region	Total Conventional LED	200 W	150 W	120 W	90 W	40 W
Central	10380	2129	1065	934	2099	4153
South	12657	2391	1310	1.310	2594	5052
East II	18199	3554	1859	1705	3714	7367
North	13242	2619	1345	1309	2690	5279
West II	13714	2707	1376	1376	2750	5505
West I	13624	2681	1392	1311	2675	5565
East I	15515	3150	1575	1342	3150	6298
Total	97331	19231	9922	9287	19672	39219

Table 2. Existing SSLS streetlights

Region	Total *SSLS*	200 W	150 W	120 W	90 W	40 W
Central	265	0	0	131	30	104
South	444	229	0	0	26	189
East II	386	163	0	154	3	66
North	210	71	0	36	0	103
West II	49	46	0	0	3	0
West I	291	102	0	81	108	0
East I	233	0	0	233	0	0
Total	1.878	611	0	635	170	462

2. Method

2.1. Proposed Methodological Framework

By combining advanced analytical techniques with an understanding of local needs and priorities the framework proposed in this manuscript identifies the key elements to which municipalities must evaluate and consider. The research methodology are illustrated in Fig. 2. The methodological process commences with field studies to understand local context and needs. These studies provide insights into the required problem-solving process. Subsequently, the urgency priority calculation for smart infrastructure implementation in each designated region is conducted, employing the Analytical Hierarchy Process (AHP). In this context, Smart Street Lighting System (SSLS) prioritization based on each SubDOT region is conducted. The output from AHP serves as the foundation for developing the model, encompassing scenario determination, cost-benefit analysis mode, and the optimization simulation, in this context will be mixed integer goal programming (MIGP). Following this, data gathering, and data running are performed. The outcomes of the data running encompass the results of optimization simulation and CBA. These results are then utilized to determine which desired smart infrastructure implantation scenario will be selected.

2.2. Existing Conditions and Literature Review for Smart Street Lighting Implementation

The primary purpose of installing streetlights is to illuminate roads and prevent traffic crashes both vehicular and pedestrian [33]. A study on street lighting in Bandung illustrates that LED lights can reduce CO2 emissions by up to 26.5% or approximately 3 tons per year [34]. Research in Nigeria indicates that with a projected lifespan of about 60,000 hours, LED lights contribute to substantial reductions in replacement and maintenance expenses, thereby enhancing operational savings. Furthermore, LED lights have minimal carbon footprints as they are 100% recyclable and contain no toxic materials, unlike conventional High-Pressure Sodium (HPS) streetlights [35].

The annual estimated social cost of nighttime crashes, specifically attributed to safety-related lighting in urban areas categorized as V, amounts to approximately $310 million. This figure represents approximately 8% of the nationwide total of approximately $3.8 billion spent on such crashes per year [36]. The improved visibility also leads to a reduction of crimes with robberies and motor vehicle theft being the most substantially reduced crimes [37], [38].

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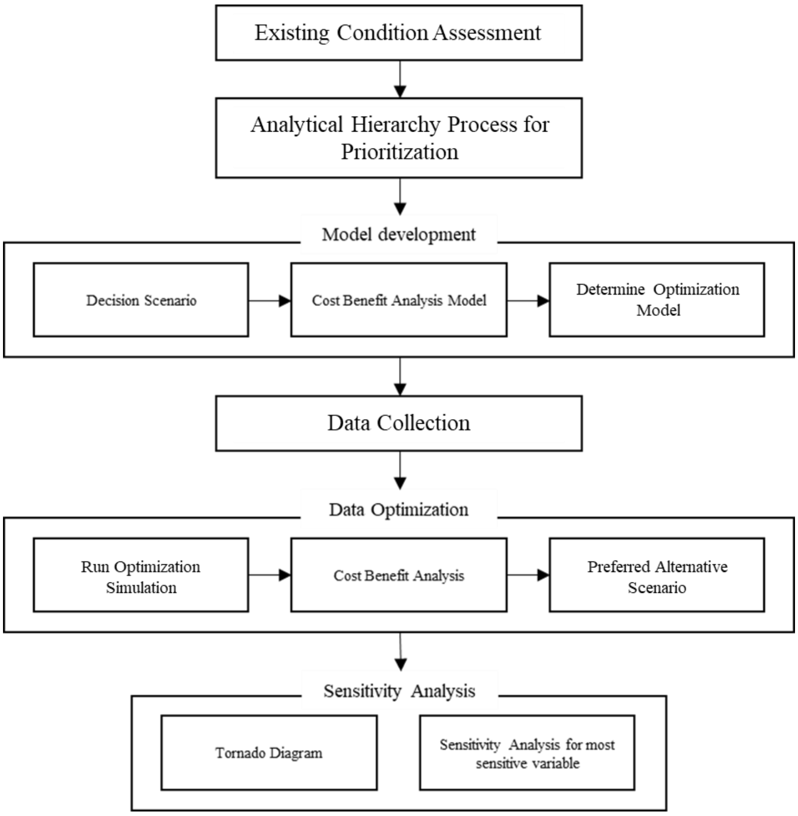

Fig. 2. Framework diagram

The Smart Street Lighting System (SSLS) is an automated and intelligent lighting control system, centralized or distributed through various IoT communication protocols, devices, and sensors. Generally, the components of the Smart Street Lighting System consist of three parts: the Lamp Unit (LU), Local Control Unit (LCU), and Control Center (CC). LU is equipped with LED lights and several supporting sensors, functioning to collect and communicate data with each other. LU can be controlled by the Local Control Unit (LCU) or the Control Center (CC). Adequate sensors must be integrated into LU to enable systematic control. Then, LCU collects data from LU using short communication protocols. CC gathers all LCU data and stores it on the server. The data on the server is visualized and analyzed for administrative purposes [39]–[41]. Automated data visualization can provide damage notifications for street lighting much faster than waiting for reports from residents.

The Mixed Integer Goal Programming (MIGP) method is the primary approach in this study. MIGP has been implemented to address various issues, examples include optimizing equipment and truck allocation considering short-term production schedules, advancing from flexible job shop scheduling problems (FJSP), and addressing even-aged forest regeneration planning problems in the Mediterranean regionf Turkey [34]. This shows the adaptability and applicability of this method for different use cases. A study by Upadhyay and Askari-Nasab (2016) aimed to optimize operations based on four desired goals for the company: maximizing production, minimizing deviations in head grade, minimizing deviations in feed tonnage to the processing plant from the desired feed, and minimizing operating cost [34]. The approach used was Mixed Integer Linear Goal Programming (MILGP), with decision variables including shovel assignments (binary), the number of truck trips (integer), production tonnage, and used slack or deviation. Decision variables consisted of integers and real sets, making the problem suitable for solving using MILGP. While this study shares similarities in method and topic, focusing on the MILGP method and allocation of goods, it does not address the feasibility study or any financial indicator scenario.

A feasibility study on SSLS was conducted by Syarafina and Gunarta [42]. This study focused on the feasibility analysis of a collaboration scheme between the Sidoarjo City Government and a third party. The study used financial analysis methods such as Internal Rate of Return (IRR), Net Present Value (NPV), Payback Period (PP), and Cost Benefit Analysis (CBA). Cost components used in the feasibility analysis can be implemented in this study. One CBA indicator used is the Benefit-Cost Ratio (BCR). The study focuses solely on feasibility analysis without considering budget constraints that necessitate optimization. In practice, the procurement cost of SSLS is significantly higher than that of Conventional LED, so the government must carefully consider the optimal proportion. Therefore, integrating optimization with cost-benefit analysis is essential.

This integration has also been done before by Ren et al. [43] using the CBA method and Mixed Integer Nonlinear Programming (MINLP). The study discusses BCR optimization in a Distributed Energy System (DEM) problem in a hotel. BCR is used as the optimization objective function. At the end of the optimization, the benefits are divided using a ratio to determine the amount of benefit for each stakeholder. The author has a similar research focus to Ren et al. [43]. The limitation of the study is the distribution of benefits using a ratio based on Ren et al.'s opinion. A more scientific weighting method is needed to determine the proportion of SSLS in each region based on stakeholder preferences. The weighting method must also be integrated with the optimization process to ensure practical and financially sound decision-making.

Research discussing stakeholder preferences with optimization is shown by Otar and Temur [44]. The issue raised is about modeling the vaccine distribution process. The model is developed using AHP and Weighted Approach Goal Programming. AHP is used for weighting each criterion, consisting of transportation costs, assignment costs, travel costs, and penalty costs. AHP results will be used as the weight of each goal in Goal Programming. This integration can be applied to this framework testing problem. AHP will be used as the author's weighting method. Therefore, the framework testing will focus on two areas: feasibility study and optimization. Three methods are used, namely Analytical Hierarchy Process (AHP), Cost Benefit Analysis (CBA), and Mixed Integer Goal Programming (MIGP).

2.3. Framework Testing

2.3.1. Analytical Hierarchy Process

The weighting criteria for each region were developed and confirmed by the officers from the SubDOT in the Streetlight and SSLS procurement division. Officers in the procurement division are responsible for determining the quantity of Public Street Lighting (PSL) and SSLS acquisitions based on the available budget. Currently, SSLS acquisitions are randomly distributed in each division. To facilitate SubDOT in the procurement process, it is necessary to conduct regional weighting with several relevant criteria. These criteria include:

- Regional Road Security

  Roads without lighting pose a risk for crime and when damaged PSL should be promptly repaired to reduce the detrimental impacts. SSLS has the potential to notify damaged lighting faster than the conventional LED.

- Regional Traffic Density

  The higher the traffic density, the higher the potential for traffic crashes. Insufficient street lighting in densely trafficked areas can contribute to crashes.

- Regional Population Density

  Higher population density increases the risk of crashes and crime. SSLS can reduce these risks by minimizing repair times through prompt indication of damage.

- Regional Accessibility

  Accessibility refers to the convenience for SubDOT personnel in replacing SSLS and accessibility for residents. Additionally, due to the limited SSLS budget, replacements are done in areas with the easiest access.

- Regional Streetlight Damage Rates

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Each region has varying levels of streetlight damage. SSLS can reduce these risks by minimizing the repair time for damaged streetlights.

These criteria have been validated by SubDOT officers through interviews conducted at the Mananggal office. Data collection for these criteria will be done through Expert Judgment from the procurement division. Each criterion will have seven alternatives, representing the regions in Surabaya.

- Central Region
- West I Region
- West II Region
- South Region
- East I Region
- East II Region
- North Region

AHP allows researchers to obtain preference results with a small number of respondents. According to Sahin and Yurdugul (2018) [45], the number of AHP respondents ranges from 2 to 100, and the inconsistency value must be less than 0.1. The AHP data collection was carried out with three experts in PSL and SSLS management at SubDOT, including the PSL Procurement Division Team, the PSL Maintenance Sub coordinator, and the PSL Procurement Sub coordinator. The AHP data processing utilized the Expert Choice 11 application.

Table 3. Regional AHP results

No	Region	PSL Procurement Division	PSL Maintenance Sub coordinator	PSL Procurement Sub coordinator	*Combined*
1	Central	0.209	0.193	0.177	0.200
2	North	0.147	0.218	0.177	0.181
3	South	0.204	0.149	0.136	0.161
4	East I	0.165	0.132	0.165	0.156
5	East II	0.136	0.118	0.148	0.126
6	West II	0.086	0.1	0.112	0.098
7	West I	0.054	0.091	0.086	0.078

Based on Table 3, the order values for each region are more uniform and consistent compared to each respondent. The inconsistency values for criteria and alternative results are below 0.1. This indicates that the expert responses are consistent. The weighting results will be used as the weighting for Goal Programming.

Based on Table 3, the combined values for each region show more uniformity and consistency compared to individual respondents. The inconsistency values for both criteria and alternative results are below 0.1, indicating that the expert responses are reliable. These combined weighting results are then used as the weights in the Goal Programming model. In this study, the weights derived from the AHP serve as multipliers (denoted as Wj) for the decision variables representing the number of SSLS to be purchased in each region. This integration ensures that the resource allocation in the Mixed Integer Goal Programming (MIGP) model aligns with the prioritized needs and budget constraints of Surabaya.

2.3.2. Scenario Formulation

To improve the damaged streetlight repair process in Surabaya, several scenarios are implementable. The lighting scheme aligns with the original conditions in Surabaya, which is 12 hours. Each scenario impacts how the SubDOT decides whether to maintain Conventional LED or switch to SSLS. In each scenario, SubDOT is obligated to replace damaged streetlights that cannot be repaired. The luminaire replacement rate is 5.34% of the total damages in each region. Several comparable scenarios included in Table 4.

Table 4. Scenario

No	Scenario	Description	Special Constraints
1	Scenario 0	No purchase of SSLS (as is model). Damaged Conventional LED is repaired or replaced	Purchasing consider subDOT budget
2	Scenario 1	All streetlights are replaced with SSLS	Purchasing does not consider subDOT budget
3	Scenario 2	Purchasing SSLS to replace the damaged Conventional LED	Purchasing consider subDOT budget
4	Scenario 3	Combination of Conventional LED and SSLS. Optimal replacement of streetlights with Mixed Integer Goal Programming optimization, considering the weights of each region	Purchasing consider subDOT budget

2.4. Mathematical Formulation

This section delves into the formulas and equations utilized within the study's framework. It provides insight into the mathematical methods employed for evaluating various aspects of street lighting management, such as cost-benefit analysis, optimization techniques, and considerations for implementing Smart Street Lighting Systems (SSLS).

2.4.1. Cost Benefit Analysis

The benefits of Public Street Lighting (PSL) calculated in this study involve social and economic aspects. Tables 5, 6, and 7 show the identification of costs and benefits of PSL. It can be surmised that Smart Street Lighting Systems (SSLS) have more benefits compared to conventional LEDs. Each benefit can be calculated using Equations 8 to 16. In terms of electricity consumption, SSLS can reduce power consumption due to scheduled blackout systems. Lights can be automatically turned off at dawn. With the decrease in power consumption, SSLS can also reduce emissions. Emission reduction is quantified in this study using carbon tax.

Table 5. Investment costs

Investment Cost	Conventional LED	SSLS
Training Cost (I_T)	-	V
Lamps Armature (I_L)	V	V
Installation Cost (I_I)	-	V

There is a cost discrepancy between the investment cost of the Conventional LED and Smart Street Lighting Systems (SSLS). Conventional LEDs do not require training costs since operators are already familiar with the handling and operation processes of Conventional LED. In contrast, SSLS requires additional training for workers to learn how to operate SSLS effectively. The equation for the investment cost is indicated in Eq. (1) – Eq. (3).

$$I_t = Training\ Frequency \times Unit\ Cost\ per\ Training \tag{1}$$

$$I_l = Number\ of\ lamps_{watt} \times Unit\ Cost\ per\ Armature_{watt} \tag{2}$$

$$I_i = Number\ of\ lamps \times Unit\ Cost\ per\ Installation \tag{3}$$

Table 6. Operational costs

Operational Cost	Conventional LED	SSLS
Electricity Cost (C_E)	V	V
Maintenance Cost (C_M)	V	V
Human Resources Cost (C_H)	V	V

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Both devices require costs for electricity, maintenance, and human resources. The difference lies in the magnitude of the costs for each. The electricity cost for SSLS will be lower due to dimming features, but it has higher maintenance costs due to increased device complexity. The human resources cost for SSLS also increases as it requires additional personnel to oversee and operate the SSLS system in each area. The equations for operational cost are shown in Eq. (4) – Eq. (7).

$$Total\ Electricity\ Cost\ (C_E) = \ Rlectricity\ Cst\ per\ KWH\ (Rp) \times Electricity\ Consumption\ (KWH) \quad (4)$$

$$Electricity\ Consumption = \sum(Power\ (KW)\ x\ Time\ (Hours)\ x\ Dimming\ (\%)\ x\ 365\ Days\ x\ \#\ Lamps \quad (5)$$

$$otal\ Maintenance\ Cost\ (C_M) = \ \sum \quad Number\ of\ Lamps_{watt} \times Unit\ Cost\ per\ Maintenance_{watt} \quad (6)$$

$$Total\ Human\ Resources\ Cost\ (C_H) = \ Number\ of\ People\ \times\ Annual\ Salary \quad (7)$$

Table 7. Benefits

Benefit	**Conventional LED**	**SSLS**
Reducing Traffic Accidents (B_A)	V	V
Reducing Crime (B_C)	V	V
Remaining Budget (B_{Re})	V	-
Decreasing Patrol and Repair Time (B_R)	-	V
Decreasing Electricity Consumption (B_E)	-	V
Decrease CO_2 Emissions (B_{CO2})	-	V

There are several differences in benefits between Conventional LED and SSLS. A benefit exhibited by Conventional LEDs is they have a lower cost for fixtures. SSLS has the advantage of a dimming system and alerts when malfunctions occur which facilitates a faster repair process. Moreover, the dimming system will decrease electricity costs, indirectly reducing emissions. The equations for benefits are explained in Eq. (8) – Eq. (17).

$$B_A = \ Loss\ \left(\frac{IDR}{Accident}\right) \times \left(\frac{Number\ of\ Accidents}{(100\%-35\%)} - Number\ of\ Accidents\right) \quad (8)$$

$$B_C = \ Loss\ \left(\frac{IDR}{Crime}\right) \times \left(\frac{Number\ of\ Crimes}{(100\%-20\%)} - Number\ of\ Crimes\right) \quad (9)$$

$$Bre\quad t = 1 = \frac{Conventional\ LED\ Amounts}{Total\ Conventional\ LED} \times\ (Budget\ per\ Year\ (IDR) - Budget\ Realization\ (IDR) \quad (10)$$

$$Bre\quad t > 2 = \frac{Conventional\ LED\ Amounts}{Total\ Conventional\ LED} \times (Operational\ Budget\ (IDR) - C_E - C_M - C_H(IDR)) \quad (11)$$

$$B_R = \frac{Conventional_{repair\ time} - SSLS_{repair\ time}}{SSLS_{repair\ time}} \times Ratio\ \frac{Failed\ Lamp}{Number\ of\ Lamps} \times Lost\ Time \quad (12)$$

$$Lost\ Time = Total\ Accidents + \ Total\ Crimes + Total\ Lost\ Night\ Economic\ Activities \quad (13)$$

$$Total\ Accidents = \ Unit\ Lost\ \left(\frac{IDR}{Accident}\right) \times (Number\ of\ Accidents) \quad (14)$$

$$Total\ Crimes = Unit\ Lost\ \left(\frac{IDR}{Crimes}\right) \times (Number\ of\ Crimes) \quad (15)$$

$$B_E = Number\ of\ SSLS \times Reduction\ of\ Electricity\ Consumption\ \left(\frac{KWH}{SSLS}\right) \times Electricity\ Cost(\frac{IDR}{KWH} \quad (16)$$

$$B_{CO2} = Number\ of\ SSLS \times Reduction\ of\ e - CO_2\ \left(\frac{kg}{SSLS}\right) \times Carbon\ Tax\ Rate(\frac{IDR}{kg\ e-CO_2}) \quad (17)$$

2.4.2. Benefit Cost Ratio Calculation

The Benefit-Cost Ratio (BCR) formula includes the variables traffic crash reduction (BA), reduction of repair time (BR), crime reduction (BC), decreasing electrical consumption (BE), and reducing CO2 emissions (BCO2). Investment costs comprise training (IT), lamps and armature (IL), and Smart Street Lighting Systems (SSLS) installations investment (II). Operational costs involve electricity (CE), maintenance (CM), and human resources (CH) expenses. The discounted factor over time (t) is denoted by 'r'. All investment, operational, and benefit values will be calculated per region. The BCR calculation equations are illustrated in Eq. (18) – Eq. (19).

$$BCR/Rayon = \frac{(Total\ Benefit)_{t=1} + \sum_{t=1}^{planning\ horizon} \frac{Total\ Benefit_t}{(1+r)^t}}{I_{t=1} + \sum_{t=2}^{planning\ horizon} \frac{(Total\ Cost)_t}{(1+r)^t}} \quad (18)$$

$$BCR\ Surabaya = \sum_{rayon=1}^{7} \frac{(Total\ Benefit)_{t=1} + \sum_{t=1}^{planning\ horizon} \frac{Total\ Benefit_t}{(1+MARR)^t}}{(Total\ Cost)_{t=1} + \sum_{t=1}^{planning\ horizon} \frac{Total\ Cost_t}{(1+MARR)^t}} \quad (19)$$

2.4.3. Mixed Integer Goal Programming

Goal Programming is the most appropriate method to determine the optimal proportion of Public Street Lighting replacement that reflects the preferences of the Surabaya Department of Transportation (SubDOT), based on the urgency level of each region. However, to suit the specific structure of the problem, the model needs to be adapted into Mixed Integer Goal Programming (MIGP). This modification is required due to the presence of decision variables with different types of constraints.

The model includes integer decision variables, which apply to the number of Smart Street Lighting Systems (SSLS) and Conventional LED units to be purchased. It also includes real-number or continuous variables, which serve as slack or deviation variables that measure how much each region deviates from the target repair time of less than 24 hours. These constraints ensure that the optimization process accounts for both the practicality of procurement and the performance objectives of each region.

- Objective Function

$$Min\ Z = \sum_{j=1}^{7} W_j \,.\, D_j^+ \,.\, Dx_j \quad (20)$$

- Decision Variable

$$X_j, Y_j \quad (21)$$

- Subject to

$$WP_j - D_j^+ + D_j^- \leq 24\ ,\ \forall j = 1, \dots, 7 \quad (22)$$

$$X_j + Y_j \leq Ye_j\ ,\ \forall j = 1, \dots, 7; \quad (23)$$

$$X_j, Y_j \in Integer,\ \forall j = 1, \dots, 7 \quad (24)$$

$$D_j^+, D_j^- \in Real,\ \forall j = 1, \dots, 7 \quad (25)$$

$$X_j + Y_j \geq F_j\ ,\ \forall j = 1, \dots, 7 \quad (26)$$

$$\left(\sum_{j=1}^{7} X_j CX_j + Y_j CY_j + Ye_j CYe_j + CXe_j\right) + FC \leq A,\ \forall j = 1, \dots, 7 \quad (27)$$

$$WP_j = \frac{TX(X_j + Xe_j) + TY(T_j - X_j - Xe_j)}{T_j}\ ,\ \forall j = 1, \dots, 7 \quad (28)$$

$$X_j, Y_j, D_j^+, D_j^- \geq 0 \quad (29)$$

Description

WP_j	Average repair time goal for region j (hours)
W_j	Weight of the goal for region j
Dx_j	Quantity of Smart Street Lighting Systems (SSLS) needed to reduce the average repair time for region j by one hour (each)
T_j	Total PSL goal in region j (each)
X_j	Total new SSLS goal in region j (each)
Y_j	Total new Conventional LED goal in region j (each)
Xe_j	Total existing SSLS goal in region j (each)

Ye_j	Total existing Conventional LED goal in region j (each
F_j	Total damaged PSLs that need replacement in region j (each)
D_j^+	Slack or excess repair time for SSLS per goal or region j (hours)
D_j^-	Slack or shortage of repair time for SSLS per goal or region j (hours)
CXe	Total cost of existing SSLS (IDR)
CYe	Cost of existing Conventional LED (IDR/Each)
CX	Cost of new SSLS (IDR/Each)
CY	Cost of new Conventional LED (IDR/Each)

2.4.4. Mixed Integer Goal Programming

The process of calculating cost-benefit analysis and mixed-integer goal programming requires several pieces of data. The data utilized for these calculations are presented in the Table 8, Table 9, and Table 10.

Table 8. CBA input data

Data Input	Value	Unit
Planning Horizon [46]	12	Years
Marr (Social Discount Rate) [47]	8.5	%
Number Of People (0 Scenario)	56	People
Number Of People (1st, 2nd, 3rd, Scenario)	84	People
Emission Factor [48]	0.7813	$\frac{Kgco2e}{Kwh}$

Table 9. Investment cost input data

Cost Component	Conventional LED	*SSLS*	Unit
Investment Cost			
Training Cost	IDR 0	IDR 40000000	IDR/Project
Streetlight Cost			
200 W	IDR 7781143	IDR 9705666	IDR /Each
150 W	IDR 5903000	IDR 8586333	IDR / Each
120 W	IDR 4715836	IDR 7524222	IDR / Each
90 W	IDR 4230441	IDR 7355044	IDR / Each
40 W	IDR 2948652	IDR 6204118	IDR / Each
SSLS Installation Cost	IDR 0	IDR 204432	IDR / Each

Table 10. Streetlight purchased distribution input data

Power	Central	South	East II	North	West II	West I	East I
200 W	19.7%	19.7%	20.5%	18.9%	20.3%	19.5%	19.8%
150 W	10.2%	10.0%	10.3%	10.4%	10.2%	10.2%	10.2%
120 W	9.6%	10.0%	9.0%	10.4%	8.6%	9.4%	9.9%
90 W	19.6%	20.1%	20.2%	20.5%	20.3%	20.4%	20.3%
40 W	40.8%	40.1%	40.0%	39.9%	40.6%	40.5%	39.9%

Table 11. Operational cost input data

Source	Conventional LED	SSLS	Unit
Electricity Cost [49]	IDR1699	IDR1699	IDR/kwh
Maintenance Costs			
200 W	IDR389057	IDR485283	IDR/Each
150 W	IDR295150	IDR429316	IDR/Each
120 W	IDR235791	IDR376211	IDR/Each
90 W	IDR211522	IDR367752	IDR/Each

Source	Conventional LED	SSLS	Unit
40 W	IDR147432	IDR310205	IDR/Each
Staffing Costs	IDR4525479	IDR4525479	IDR/Staff

Table 12. Benefits input data

Benefit Type	Conventional LED	*SSLS*	Unit
Fatal Crashes per PSL [50], [51]	0.0043	0.0043	Crashes/PSL
Cost per Crash [52]	IDR342556620	IDR342556620	IDR/Crash
Crimes per PSL [53]	0.00672	0.00672	Crime/PSL
Cost per Crime [54]	IDR68969100	IDR68969100	
Repair Time Reduction		IDR5852933	IDR/PSL
Electrical Cost Reduction (kw)			
0.2	IDR0	IDR341180	IDR/PSL
0.15	IDR0	IDR255885	IDR/PSL
0.12	IDR0	IDR204708	IDR/PSL
0.09	IDR0	IDR153531	IDR/PSL
0.04	IDR0	IDR68236	IDR/PSL
Carbon Emission Reduction (kw)			
0.2	IDR0	IDR4705	IDR/PSL
0.15	IDR0	IDR3528	IDR/PSL
0.12	IDR0	IDR2823	IDR/PSL
0.09	IDR0	IDR2117	IDR/PSL
0.04	IDR0	IDR941	IDR/PSL
0.2	IDR0	IDR4705	IDR/PSL

Based on the data results above, data processing was carried out to obtain the variables in the Mixed-Integer Goal Programming (MIGP). The processed variables are presented in Table 11 and Table 12. The processing aims to facilitate the optimization process of MIGP.

Table 13. Investment value

PSL Cost		*Existing SSLS*	*New SSLS*	Existing Conventional LED	New Conventional LED
Region (j)		CXej	CXj	CYej	CYj
1	Central	IDR260362433	IDR9408561	IDR1153538	IDR5814693
2	South	IDR593209343	IDR9363895	IDR1139555	IDR5752476
3	East II	IDR559797060	IDR9369631	IDR1140367	IDR5761662
4	North	IDR248180565	IDR9388561	IDR1147653	IDR5787224
5	West II	IDR93794849	IDR9381378	IDR1145429	IDR5778732
6	West I	IDR415727608	IDR9369819	IDR1141000	IDR5764191
7	East I	IDR295419055	IDR9389278	IDR1146359	IDR5789155
Units		/Region	/PSL	/PSL	/PSL

Table 14. Damage PSL each region

	Region (j)	1 *Central*	2 *South*	3 *East II*	4 *North*	5 *West II*	6 *West I*	7 *East I*
Damaged PSL	Fj	535	652	938	682	707	702	799

Table 15. Mixed integer programming input data conversion (Dxj)

Data Input	Value	Unit
1	Central	252,43
2	South	310,67
3	East II	440,72
4	North	318,99
5	West II	326,37
6	West I	329,97
7	East I	373,44

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3. Results and Discussion

The results and discussion section of the study provides a comprehensive analysis of the findings and their implications for the management of street lighting in Surabaya. It offers insights into the effectiveness of Smart Street Lighting Systems (SSLS) implementation.

3.1. Optimization Results

The optimization shows that the Z result is 5,115.21. The total purchase of Smart Street Lighting Systems (SSLS) and new Conventional LEDs is 11.917 and 5,015 respectively. The highest proportion of SSLS purchases is for the Central region with 5,457 SSLS. The purchase quantity in the central region represents 45.79% of the total overall purchase. The is due to the high weighted time factor that was attributed to the Central region. Next, the optimization results were processed to obtain the Benefit-Cost Ratio (BCR).

Table 16. MIGP optimization results

Goal (j)	**Region**	**Damaged PSL - Replacement (Fj)**	***Decision Variable***		***Variable Deviation***		**Z**
			New SSLS (Xj)	***New Conventional LED (Yj)***	***Overachieved Time (Dj+)***	***Time to Unit Conversion (Dj+. Dxj)***	
1	CENTRAL	535	5457	0	0.002	0,60	5115,21
2	SOUTH	652	652	0	19.142	5 946.91	
3	EAST II	938	938	0	19.666	8667.04	
4	NORTH	682	2664	0	13.660	4357.61	
5	WEST II	707	707	0	20.354	664280	
6	WEST I	702	700	2	19.667	6489.51	
7	EAST I	799	799	0	19.907	7433.90	
Budget Remainder		IDR889414					

3.2. Overall Cost Benefit Analysis

After obtaining results from the optimization, the next step is to calculate the BCR and repair time in each scenario. Three items, namely budget availability, BCR, and fulfillment of repair time, will be determined to identify the ideal scenario.

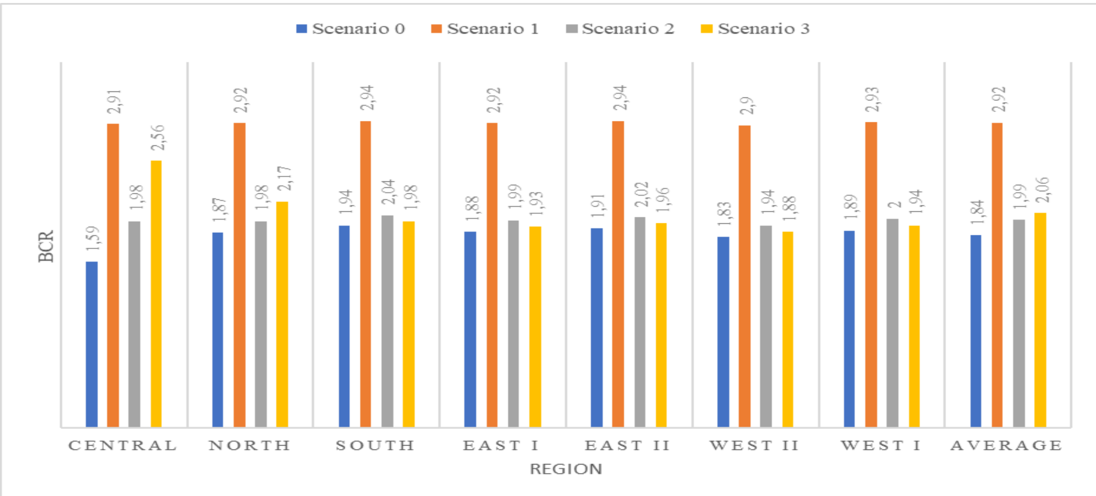

Fig. 3. Scenario benefit cost ratio

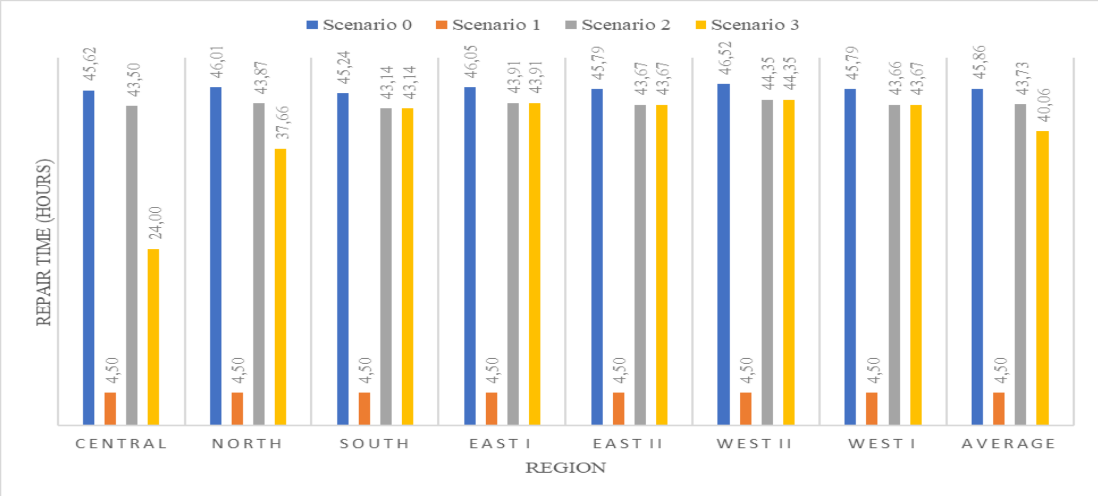

Fig. 4. Scenario repair time

Table 17. Cost for each scenario

Description	Scenario 0	Scenario 1	Scenario 2	Scenario 3
Investment (million IDR)	23231.12	749666.03	38664,64	91945.46
Operational Cost (million IDR)	117206.52	115646.52	118259,30	118053.65
Benefit (million IDR)	267582.04	601519.64	271886,16	247432.55
Remaining Budget (million IDR)	69562.36	-655.312.55	53.076.06	0.89

The scenario with the highest Benefit-Cost Ratio (BCR) based on Fig. 3 is scenario 1, followed by scenario 3. Scenario 1 has an exceptionally high BCR because it has a proportion of 100% for Smart Street Lighting Systems (SSLS). The BCR for Surabaya in scenario 1 is 2.92. In scenario 3, the BCR for Surabaya is 2.06. In scenario 2, regions other than North and South have higher BCRs than in scenario 3. This is because the remaining budget benefits are distributed to each region and are associated with Conventional LED. However, each region in scenario 3 still has a BCR greater than one, making it economically viable.

Examining the average repair time in Fig. 4, scenario 1 is the only scenario that adheres to the repair time Key Performance Indicator (KPI) requirement. The average repair time for Surabaya in scenario 1 is 4.5 hours. The second-best average repair time is in scenario 3, with a value of 40.06 hours. In scenario 3, the Central region has a repair time of 24.002, which is very close to the average repair time. Scenarios 0 and 2 repair times significantly exceed SubDOT's repair time KPI. Therefore, scenario 1 remains the scenario with the best metric output.

Subsequently, both indicators are compared to see which scenario falls within the SSLS budget. The budget is a decisive indicator for the decision-making of each scenario. The procurement and maintenance process of SubDOT Surabaya's Public Street Lighting (PSL) still focuses on the budget provided by the City Government. SubDOT does not have other income or funding sources. Therefore, all scenarios must have realizations below the budget value set at IDR 210 billion. According to Table 13, Scenario 1, with the best indicators, has a budget realization of IDR 865.3 billion. This budget exceeds the available budget, with an excess realization of IDR 655.3 billion. Therefore, scenario 1 is not feasible for SubDOT Surabaya.

The scenario with the second-best indicators is Scenario 3, optimized using Mixed Integer Goal Programming (MIGP). In the optimization process, the purchase of new SSLS and Conventional LEDs is based on the priority of meeting the repair time KPI in each region. The budget realization in scenario 3 does not exceed the budget value, which is IDR 209,999,110,586. The PSL budget still has about IDR 889,414 in remaining costs. The total budget realization is used to purchase 11,917 new SSLS and 2 Conventional LEDs. This purchase results in a proportion of Conventional LED to SSLS in Surabaya of 86.1% to 13.1%. Therefore, scenario 3 is the best scenario for SubDOT.

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The rationale for selecting Scenario 3 (Table 16) is strengthened by evaluating trade-offs between economic viability, operational performance, and policy feasibility. While Scenario 1 offers the most technically optimal outcome, its high investment cost limits practical implementation. A similar challenge is observed in other studies where full-scale SSLS deployment, despite showing high long-term returns, is often hindered by initial capital constraints [42]. Furthermore, the integration of cost-benefit indicators into multi-objective optimization models, as demonstrated in energy and infrastructure projects, provides a more balanced decision framework by considering stakeholder priorities and financial limitations [55]–[57]. Studies conducted have also employed benefit-cost optimization for smart lighting using real-time traffic and environmental data, reinforcing the importance of contextual and data-driven planning [58].

Beyond technical optimization, the policy feasibility of scenario implementation is equally critical. Investment strategies and performance-based financing can mitigate budgetary risks while maintaining service quality [59]–[61]. Additionally, the role of smart lighting in enhancing public safety and energy savings in low-income urban areas, suggesting that socio-economic impact should also be considered alongside technical efficiency [62], [63]. These insights reinforce that Scenario 3, while not optimal in every metric, offers a pragmatic balance between performance gains and affordability, particularly in resource-constrained municipal environments.

MIGP optimization aims to obtain the purchase of new SSLS and Conventional LEDs based on SubDOT's preference for meeting the repair time KPI. The optimization results from Goal Programming may not provide the optimal BCR and repair time, but will provide results that are most aligned with SubDOT's preferences or priorities of stakeholders. The Weighted Approach is used in Goal Programming, which helps SubDOT determine the quantity of SSLS replacement in each region based on regional weighting. Regional weighting is the result of calculations using the Analytical Hierarchy Process (AHP). The AHP weights indicate the potential impact due to the length of PSL repair handling. The higher the AHP-weighted region, the higher the risk of losses in that region. Therefore, MIGP will produce the most satisfactory quantity of new PSL per region for SubDOT.

Weighting in MIGP allows the optimized BCR to not always be ideal (Equation 20). The correlation between MIGP and CBA is the number of SSLS that reduces the average repair time (Equation 12). The more SSLS, the higher the value of the BCR benefit of reducing repair time in the optimization scenario. This benefit will expand and result in a higher BCR. The positive correlation between the quantity of SSLS and the benefit of repair time reduction is shown in subsection 6.3. If there is no weighting, the result will follow the lowest SSLS unit conversion factor from hours or region with highest SSLS proportion. The SSLS unit conversion factor indicates the effort SubDOT must pay to reduce the average repair time of a region (Table 14). The lower the conversion factor, the lower the cost required to make a region meet the KPI. This condition allows Surabaya to achieve a more optimal BCR, but it does not align with SubDOT's preferences.

Table 18. Slack MIGP

Goal **(j)**		**Lack of *SSLS***	**Repair Time Target**
1	CENTRAL	1	23,998
2	SOUTH	5.947	24,000
3	EAST II	8.667	23,998
4	NORTH	4.358	23,999
5	WEST II	6.643	23,999
6	WEST I	6.490	23,999
7	EAST I	7.434	24,000
Total		39.539	23,999 (rata-rata)

One piece of information obtained from the results of Mixed Integer Goal Programming (MIGP) is the slack or deviation variable for each goal or region (Table 17). The deviation variable, in terms of hours, is converted into SSLS units. This conversion result indicates the quantity of Public Street Lighting (PSL) needed to meet the KPI of average repair time in each region. The added SSLS can be validated for repair time using Eq. (21). Based on Table 16 there is a shortfall of 39,539 SSLS to meet the repair time KPI in each region. The proportion of new SSLS replacement indicates that achieving the average repair time requires a proportion of 53.76% SSLS. The estimated budget shortfall needed for SubDOT to meet the KPI of average repair time in each region is IDR 303,306,218,345. The obtained Benefit-Cost Ratio (BCR) is 2.584. This means the project is financially feasible because the BCR value is greater than one. One effort SubDOT can make to address the budget shortfall is through collaboration with a third party.

Several costs and benefits have a significant impact on the total cost category. In investment costs, the percentage of lamp armature costs increases by 26.1%. This is because of the additional installation costs for Smart Street Lighting Systems (SSLS). In scenario 0, damages would be replaced with Conventional LED, not affecting the SSLS installation cost component. In operational costs, the addition of SSLS will reduce electricity costs due to the dimming system in SSLS (Equation 16). The reduction in electricity costs is IDR 2,052,608,792 per year. However, there are additional maintenance costs for SSLS (Equation 6). SSLS has a higher potential for damage due to its higher system complexity [64], [65]. Therefore, this cost affects the additional percentage of maintenance costs [66], [67].

The most prominent benefits in scenario 0 are a 54.02% reduction in fatal accidents (Equation 8) and a 26.00% remaining budget (Equation 10 dan 11). The remaining budget has a significant value because the procurement cost of SSLS is not optimized. In scenario 3, the budget value is optimized to meet the repair time KPI. This makes the percentage of the remaining budget approach zero. The reduction in repair time will affect the repair time itself. Conventional LED and SSLS have a significant difference in repair time, which is 42.17 hours. The value of the benefit of a substantial reduction in repair time indicates the risk of accidents (Equation 8) and crimes (Equation 9) for each difference in repair time between Conventional LED and SSLS. Thus, the benefits of reducing repair time (Equation 13) in scenario 3 have a high percentage, namely 22.14%. The percentage of the benefits of reducing repair time will continue to increase with the addition of SSLS in each region.

Despite the model’s integration of cost-benefit analysis and optimization, it has several key limitations affecting its robustness and applicability. It uses fixed values for costs, benefits, damage rates, and repair times, which do not capture real-world uncertainties like fluctuating electricity prices, maintenance costs, or unexpected failures. Budget limits may restrict the scale and timing of implementation. The model’s assumptions exclude complex external factors and sudden policy changes, which reduces its real-life accuracy. It is sensitive to variables such as electricity costs, influencing financial feasibility. The model does not consider institutional, operational, or policy barriers, nor social aspects like public acceptance, equity, or long-term behavior, which are vital for sustainable planning. It assumes uniform compliance across regions, ignoring differences in local capacity and resources that affect effectiveness and fairness. Finally, practical challenges like stakeholder coordination and unexpected issues are not fully addressed, which may impact project success and sustainability.

Scenario 3 reflects a practical implementation of smart city principles, balancing cost-efficiency, service performance, and stakeholder priorities. The integration of AHP and MIGP enables data-driven, region-sensitive planning that accounts for varying repair needs and risk exposure as an essential feature for cities operating under strict budget constraints [68]. By prioritizing infrastructure upgrades in high-impact areas, the scenario improves operational outcomes while ensuring equitable service distribution. In addition to addressing current performance gaps, the expanded deployment of smart lighting infrastructure lays the groundwork for future digital services, including traffic regulation, public safety monitoring, and environmental sensing [69]. Scenario 3 therefore represents a strategic step toward Surabaya’s long-term vision of integrated and adaptive urban infrastructure.

3.3. Sensitivity Analysis

Sensitivity analysis is employed to understand the impact of changes in specific variables on the desired results or output [70]–[73]. Sensitivity analysis will be conducted on the selected scenario, namely scenario 3. The variable to be altered is an uncontrollable variable. The uncontrollable

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variables selected are based on the most significant cost and benefit components. Each variable will undergo sensitivity analysis with a minimum range of minus 15% and a maximum range of plus 15%. The influence of each variable change on the BCR value for Surabaya will be examined. Each change will be summarized, and a tornado diagram will be created. A tornado diagram is a type of chart used to illustrate the variation or sensitivity of a variable to the desired results or output being analyzed.

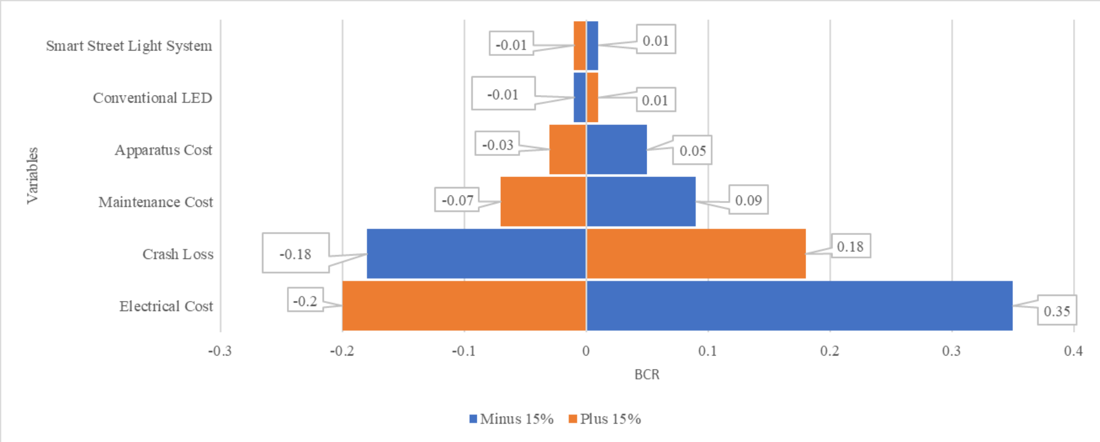

Fig. 5. BCR Sensitivity Analysis with Tornado Diagram

Based on Fig. 6, the most sensitive and impactful variables on the Benefit-Cost Ratio (BCR) are electricity costs and accident losses. Electricity costs constitute approximately 75% of the cost component when viewed solely from the operational expenses. Therefore, most costs from years 2 to 11 are electricity costs. A 15% decrease in electricity costs will increase the BCR by 0.35. This indicates that electricity costs have a negative correlation with the BCR. The higher the electricity costs, the lower the BCR. A decrease in electricity costs has higher sensitivity compared to an increase in electricity costs. A 15% increase in electricity costs will decrease the BCR by 0.20.

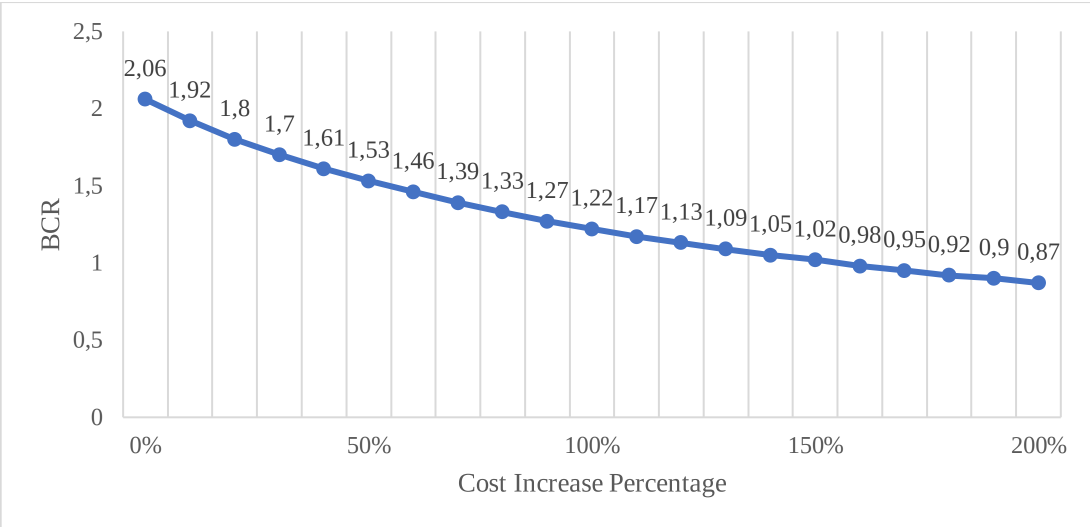

Fig. 6. Cost sensitivity analysis toward BCR

Further sensitivity analysis was conducted on the electricity cost variable. By creating a graphical analysis, the impact on the BCR value and its decreasing trend can be observed. Based on Fig. 6, the BCR will become infeasible or have a value less than one when the electricity cost increases by 160%. Surabaya's BCR will be infeasible when the electricity cost reaches IDR 2,719 per kWh. The required increase to render Surabaya's BCR infeasible is extremely high. Therefore, the risk of infeasibility in the SSLS project with scenario 3 is relatively low. Thus, electricity costs and other variables have less impact on the BCR of the Surabaya City SSLS replacement project.

The sensitivity analysis and findings from the SSLS implementation in Surabaya suggest clear policy directions. Surabaya should adopt procurement strategies aligned with Scenario 3, which balances cost and performance effectively, ensuring efficient use of public funds and maximizing system benefits. Formalizing this procurement method as a Standard Operating Procedure (SOP) is recommended, and its adaptation by other cities with similar conditions could support standardization in smart city infrastructure development. This approach is supported by studies emphasizing the importance of integrated procurement frameworks for scalable and cost-effective smart city technologies . Additionally, it aligns with findings on governance practices that enhance urban digital infrastructure deployment [74]–[76].

Moreover, it is essential for authorities to regularly update and employ the analytical framework developed in this study to guide ongoing SSLS procurement, especially after reaching key performance goals such as repair times under 24 hours. The sensitivity results highlight the need to monitor electricity costs, as they significantly influence the system's benefit-cost ratio. Keeping cost increases within 150% is advisable; if costs exceed this threshold, subsidies or financial incentives may be necessary to maintain economic viability. This condition is reinforced by research documenting the impact of operational cost management on the sustainability of smart infrastructure projects [77]–[79]. Ultimately, these recommendations stress the importance of evidence-based, adaptable policies capable of addressing cost variability and system performance to sustain long-term smart city infrastructure success.

3.4. Model Adaptability

The smart city infrastructure implementation framework presented in this study is designed for high adaptability, allowing it to be effectively applied in various urban contexts beyond the initial case. Its modular and flexible structure empowers local decision-makers to customize essential components such as procurement methods, data collection techniques, performance metrics, and cost-benefit analysis tools to align with the unique characteristics and needs of their city or service. This adaptability ensures that the framework is not only a technical model but also a comprehensive decision-support system tailored to diverse institutional and regulatory environments.

SubDOT of other cities or regencies can implement the research methodology by adjusting it to their local management conditions. The implementation requires tailoring data input for optimization models such as MIGP and CBA. Key variables for adaptation include:

- Preferences and the number of regions in each city/regency
- The number of existing Conventional LED and SSLS
- Frequency and volume of repair and damage activities for both types of PSL
- Repair time KPI specific to each city/regency
- Local budget allocations
- Available human resources (SDM) for maintenance
- Cost components unique to the local context
- Statistics of accidents and crimes relevant to street lighting needs

By systematically customizing these variables, cities or regencies can optimize the framework's application to reflect their operational realities, resource availability, and safety priorities, ensuring a data-driven and context-sensitive approach to urban infrastructure management [80], [81].

4. Conclusion

Based on the MIGP optimization results, the acquisition of new Smart Street Light System (SSLS) amounts to 11,915 units. The percentage distribution of SSLS purchases out of the total 11,915 for the Central, North, South, East I, East II, West II, and West I districts, respectively, is 45.79%, 22.35%, 5.47%, 6.70%, 7.87%, and 5.93%. The purchase of Conventional LED comprises 2 units, all

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allocated to the West I district. The most optimal proportion of Conventional LED and SSLS is 86.1% and 13.9%, respectively. The BCR for scenario 3 is financially viable with a value of 2.059. If Surabaya Department of Transportation (SubDOT) aims to meet the average repair time KPI in each district, an additional replacement of 39,593 new SSLS is required, with a funding shortfall of IDR 303,306,218,345.

The failure of Scenario 1, despite its high BCR, shows that the best technical solution isn't always practical due to budget limits. Surabaya Government need to focus not just on cost-benefit but also on what can realistically be funded. Scenario 3 proves that balancing performance with affordability leads to better, implementable decisions. This case teaches that successful planning requires considering financial constraints alongside technical goals to ensure policies are both effective and feasible.

While the proposed framework demonstrates strong potential in optimizing smart infrastructure planning, certain limitations remain inherent to its current scope. The use of fixed input parameters—such as electricity prices, maintenance costs, and failure rates—while appropriate for strategic-level analysis, may not fully reflect the dynamic nature of real-world conditions. Moreover, institutional and social dimensions, including governance capacity, stakeholder coordination, and public acceptance, present critical variables that warrant further integration. Enhancing the model through adaptive mechanisms and policy-oriented extensions will improve its robustness and applicability across diverse urban contexts.

Sensitivity analysis indicates that electricity costs have the highest sensitivity among the six tested variables. Electricity costs have a negative correlation with the BCR. Every 15% increase in electricity costs will decrease the BCR by 0.2. The electricity cost variable does not significantly influence the BCR, requiring a 160% increase in electricity costs to render Surabaya's BCR infeasible.

In conclusion, the development of optimization frameworks for smart city infrastructure is not only important but also urgent, particularly for developing countries facing the dual challenges of rapid urbanization and limited resources. By leveraging innovative technologies and analytical methodologies, these frameworks offer a path towards more sustainable, resilient, and inclusive urban development. As cities around the world embark on their smart city journeys, it is essential to ensure that these efforts are guided by robust frameworks that prioritize the needs and aspirations of all citizens. The optimization study on smart light implementation in Surabaya holds as a successful implementation of this framework for other developing countries lacking a smart infrastructure system. It is hoped that this new framework can serve as a practical guide for other cities beyond Surabaya. The effort to transition Surabaya into a Smart City beginning with an implementation of the smart infrastructure framework provides a template for decision-makers in other developing nations to tailor and implement smart lighting solutions and make steps to becoming a smart city effectively, considering their specific circumstances and constraints.

Future directions for this research include integrating real-time data into the optimization model and exploring sustainable financing mechanisms to support broader smart city implementation, as real-time data can enhance responsiveness to dynamic urban conditions—such as traffic patterns or energy usage—while sustainable financing (e.g., green bonds or public-private partnerships) can help overcome budget constraints and enable large-scale, long-term infrastructure investments.

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