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A LIFE CYCLE COST ANALYSIS FRAMEWORK TO COMPARE FIXED SENSOR NETWORK AND ON-DEMAND ROBOT-BASED DATA COLLECTION IN INDOOR BUILDING ENVIRONMENTS

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SUMMARY: *Indoor environmental quality (IEQ) monitoring is crucial for occupant well-being and building performance optimization, with data collection methods significantly impacting the effectiveness and feasibility of monitoring systems. Fixed wireless sensor networks (FWSN) have been widely used for IEQ data collection and monitoring; however, they face several challenges, such as tedious installation and maintenance, as well as high power consumption. To address these limitations, mobile sensor robots (MSR)-based data collection systems were suggested as a viable alternative through various studies. Nonetheless, a comparative analysis of the economic feasibility of both indoor data collection methods remains unexplored. In this study, a comprehensive Life Cycle Cost Analysis (LCCA) framework was developed to compare the financial viability of FWSN and MSR systems for indoor ambient temperature data collection, incorporating building characteristics, cost components of data collection methods, as well as both deterministic net present value (NPV) calculations and probabilistic Monte Carlo simulations to account for uncertainties. This study, therefore, contributes to a practical methodology to guide financial and operational decisions for indoor IEQ monitoring systems through a systematic LCCA framework that combines deterministic and probabilistic analyses, along with sensitivity and heatmap visualizations. The methodology was validated through a case study involving three commercial complexes of varying sizes in Mumbai, India, with sensitivity analysis and heatmap visualization employed to investigate the influence of key parameters such as floor space, discount rate, sensor density, and data collection intervals. Results revealed that FWSN systems were more feasible for smaller buildings, with an NPV of around 35 million INR compared to an NPV of around 90 million INR for MSR, while MSR systems proved more cost-effective for larger floor spaces with an NPV of around 90 million INR versus 140 million INR for FWSN. The sensitivity analysis and generated heatmaps identified multiple breakeven points between the two systems at different values of investigated parameters, highlighting the critical need to accurately identify specific conditions and characteristics of a project during the initial stages to employ the most cost-effective system. Some limitations were present in this study, such as the assumptions of uniform floor space distribution, fixed labor requirements, and robotic price variability, which may not reflect more complex building environments. The developed framework serves as a valuable decision-making tool for facility managers to evaluate and select optimal data collection strategies based on specific building characteristics and monitoring requirements.*

KEYWORDS: *indoor environmental quality, fixed wireless sensors, mobile sensor robots, life cycle cost analysis, net present value, monte carlo simulation.*

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1. INTRODUCTION

Humans usually spend close to 90% of their lifetime in public and private indoor environments such as offices, homes, schools, airports, shopping malls, hospitals, and theatres (Klepeis et al., 2001; Cincinelli and Martellini, 2017). Poor indoor environmental quality (IEQ) has the potential to cause adverse health effects to the occupants, thereby affecting productivity. For example, several studies have shown that poor IEQ resulted in reduced productivity among workers, as well as impacted the cognitive abilities of students in schools and universities (Wargocki et al., 2006; Shan, Melina and Yang, 2018; Mujan et al., 2019). Improving the IEQ has been proven to enhance various aspects of humans' experience, whether at offices, schools, or other establishments, particularly when examining the life-cycle impact of such improvements. For instance, Fisk et al., 2012 provided quantitative estimates of eventual benefits and costs of providing different amounts of outdoor air ventilation in offices that far exceeded energy costs as it significantly improved worker health and performance. Moreover, using a Life Cycle Cost Analysis (LCCA) approach, (Shan, Melina and Yang, 2018) studied the effects of indoor environmental quality on students' wellbeing and performance by comparing two side-by-side tutorial rooms with different ventilation settings in Nanyang Technological University, Singapore. Ventilation settings that offered more comfort to the students resulted in avoided sick leaves and increased average marks.

These studies stressed a balanced approach that, along with building energy and resource efficiency, was also important to consider humans' well-being and performance. To improve the comfort of occupants and increase building performance, it is important to optimize the IEQ of a building by collecting, managing, and analyzing real-time data efficiently. However, collecting data manually limits the capability to collect large amounts of data, eventually restricting the performance metrics (Wang et al., 2010; Raftery, Keane and Costa, 2011). Therefore, in newer buildings, wired/wireless sensors are installed, calibrated, and integrated with building systems before the operation and maintenance phase as part of the building automation system (Österlind et al., 2007; Hayat et al., 2019; Messung Group: building automation & controls, 2025). Several studies investigated the use of real-time indoor quality monitoring using spatio-temporal data from sensors mounted at different locations in a building (Kumar et al., 2016; Van Tran, Park and Lee, 2020). However, few drawbacks to the existing fixed sensor techniques include complex design requirements as they can disturb the aesthetics of the building (Raffler, Bichlmair and Kilian, 2015), tedious installation and maintenance due to intense calibration, manual supervision owing to the threat from rodents chewing off the sensor wires (Wang, Liu and Sun, 2010), extent of space that can be monitored (Demirbas, 2005; Vlissidis et al., 2008), as well as power consumption issues and limited information storage capacity (Bhadauria, Tekdas and Isler, 2011).

To eliminate such challenges, novel methods have been developed incorporating the advancement of technology in the automation sector. Existing studies in the field of mobile robot-based indoor data collection were performed in order to develop a feasible approach (Mantha, Menassa and Kamat, 2016; Lee et al., 2020). Accordingly, a mobile platform-based data collection process that uses a mobile indoor robot equipped with onboard sensors was proposed by several previous studies (Bhadauria, Tekdas and Isler, 2011; Mantha et al., 2020). As per this proposed technique, mobile robots are capable of navigating in a known or unknown indoor environment with the help of various sensors and computing capabilities. The major steps in the suggested method involved robotic navigation along with localization, data collection, and geotagging. One of the main advantages of this data collection method is that it eliminates the need for installing the same set of sensors in different locations of existing buildings (Mantha et al., 2020). Even though research has proved the technical feasibility of mobile robot-based data collection, for any facility to be deployed in practical applications, it is very important to capture the economic feasibility perspective, which has not been explored.

To address this gap, the present study compared the LCCA of a fixed wireless sensor network (FWSN) and mobile sensor robotic (MSR) data collection methods. Although previous studies involved several similar implementations in the context of their technical abilities, such as locomotion, navigation, and localization, none of them addressed the financial comparison of these systems. This makes it challenging to evaluate their respective implementation potentials. Therefore, this study explicitly poses the research question: Under what conditions does an MSR system become more economically feasible than an FWSN for indoor environmental quality monitoring? Given the significant emphasis on addressing the challenge of poor IEQ and to achieve a quality indoor environment that has optimal human comfort, including minimal noise disturbance, comfortable temperature levels, relative humidity, and reduced levels of pollutants (Karanika-Murray et al., 2021), conducting a rigorous life cycle cost comparison is critical. Such comparison helps stakeholders understand variations between estimated and actual costs, providing valuable guidance during the programming phase to evaluate alternative building features and systems that enhance overall IEQ and building performance, ultimately serving as a robust asset management tool.

The specific objectives of this study were to: (1) develop a comprehensive LCCA framework for comparing the financial feasibility between FWSN and MSR systems for indoor ambient temperature data collection, explicitly capturing data uncertainties through probabilistic Monte Carlo simulations and providing intuitive results via sensitivity analyses and heatmap visualizations; and (2) validate the developed framework through a detailed case study involving three commercial building scenarios. Initially, required inputs for the LCCA including initial, operational and maintenance (O&M), replacement, and disposal costs, were defined for both data collection methods based on literature and market insights. LCCA outputs were computed using both traditional deterministic methods and probabilistic Monte Carlo simulations to robustly account for uncertainties in the input data. Furthermore, the influence of various parameters on the outputs of the developed LCCA framework was explored through sensitivity analysis complemented by heatmap visualizations. The present research significantly advances the field by explicitly coupling robust probabilistic modeling with clear visualization techniques, thereby providing a unified, transparent, and accessible decision-making framework. Ultimately, this methodological contribution aims to assist facility managers and stakeholders in clearly identifying relationships between input variables and determining the most economically feasible and practical data collection approach for enhancing the management of IEQ parameters in buildings.

2. LITERATURE REVIEW

A comprehensive literature review was conducted to examine several key areas relevant to the present study. First, the current state and challenges of different data collection methods in building environments are reviewed, highlighting the technical characteristics and operational considerations of both FWSN and MSR systems. Second, a review of LCCA's methodology and framework is provided to establish the theoretical foundation for the comparative analysis. Third, various applications of LCCA across different infrastructure projects are discussed to understand established methodologies and insights. Fourth, the review further investigates specific applications of LCCA in building systems and sensor networks, concluding the research gap that is addressed in the present study.

2.1 Data Collection Methods in Building Environment

The growing complexity of modern buildings and increasing demands for occupant comfort, energy efficiency, and operational optimization have made environmental data collection crucial in building management. Traditional building monitoring relies heavily on FWSN to collect various environmental parameters such as temperature, humidity, air quality, and occupancy data (Rawat et al., 2014) . These sensor networks typically require careful placement planning to ensure adequate coverage while minimizing the number of sensors needed. Studies have shown that optimal sensor placement can significantly impact both data quality and system costs (Hassani and Dackermann, 2023). However, fixed sensors have inherent limitations in their ability to adapt to changing building configurations or monitoring needs, and their installation often requires significant infrastructure modifications (Ko and Lau, 2009).

In recent years, robot-based data collection has emerged as an alternative or complementary approach to fixed sensor networks. Mobile robots equipped with environmental sensors offer several advantages, including flexible coverage patterns, adaptable monitoring schedules, and the ability to access hard-to-reach areas (Rao et al., 2022). These MSR platforms can be programmed to follow optimal paths for data collection, potentially reducing the total number of sensors needed while maintaining comprehensive coverage (Fu et al., 2025). Research has demonstrated that mobile robots can effectively collect environmental data with comparable accuracy to fixed sensors while offering greater spatial resolution through their movement capabilities (Yang et al., 2023). However, robot-based systems also present their own challenges, including path planning complexity, battery life limitations, and the need for sophisticated navigation systems in dynamic indoor environments (Grzonka, Grisetti and Burgard, 2012).

The choice between FWSN and MSR often depends on various factors, including building layout, monitoring requirements, and resource constraints. These contextual factors directly correspond to the key quality and operational dimensions laid out by center for disease control and prevention (CDC) such as data accuracy, completeness, and resource availability (Kidder et al., 2024). For e.g., resource constraints such as labor or equipment directly relate to the resource availability dimension. Similarly, building layout and monitoring requirements such as building zone identification (e.g., building zone segregation based on mechanical, electrical, and plumbing (MEP) systems), frequency (e.g., every 30 minutes) and granularity (e.g., zone or room level) relate to completeness and timeliness. Further discussion regarding how and why these factors were incorporated into the analysis is discussed in detail in the methodology section. Some studies have suggested hybrid approaches that combine both methods to leverage their respective advantages (Alsafery, Rana and Perera, 2023). While both approaches have demonstrated technical feasibility, their financial implications over the entire life-cycle remain poorly understood. The significant differences in initial investment, operational costs, maintenance requirements, and system longevity between these two approaches necessitate a comprehensive economic analysis framework. Therefore, the LCCA emerges as a suitable tool for this comparison, as it can account for both immediate and long-term financial implications of each system while considering various cost components throughout their operational life.

2.2 LCCA Methodology

As the title suggests, LCCA is a method to assess the total cost of any project facility ownership by considering the costs involved in various life cycle phases. It is used to compare various options capable of performing similar tasks by analyzing the economic impact over the life of each option (Lu et al., 2023). For example, in the context of this study, LCCA considers all costs such as recurring costs, non-recurring costs, salvage value, and fixed costs. LCCA is especially beneficial when project alternatives that fulfil the same performance requirements but differ with respect to initial, O&M, as well as replacement and disposal costs have to be compared in order to select the one that maximizes net savings (Shankar Kshirsagar, El-Gafy and Sami Abdelhamid, 2010; Bochare, Dagliya and Kadam, 2024). In general, O&M costs are annually recurring costs, and replacement and disposal costs are incurred at the end-of-life cycle of the facility. These costs, also referred to as cash flows, are incurred at different times during the life cycle phase of a facility. To make cash flows time-equivalent, the LCCA method converts them to effective values by discounting them to a common point in time, typically to the present date (a.k.a. present value). Once all the costs are estimated, the Net Present Value (NPV) can be obtained for each alternative, and further conclusions can be drawn. Conventionally, costs resulting in the outflow of cash are taken to be negative, and the inflow of cash is taken to be positive (Fuller, 2010). The potential of such an analysis has been significant in evaluating different technologies and applications, considering that an owner's perspective on building design has gone beyond design and construction facilities. To better understand how LCCA can be applied, it is valuable to first examine its successful applications across various infrastructure projects.

2.3 Applications of LCCA in Infrastructure and Built Environment

Application of LCCA can be found in various fields of infrastructural projects such as transportation (Chan et al., 2008), water pipelines (Thomas, Mantha and Menassa, 2016), and commercial and institutional buildings (Ozsariyildiz and Tolman, 1998). Results from these studies illustrated that even though a specific alternative has initial economic benefits due to lower procurement costs, over the long run, it could tend to get costlier and vice versa. (Dandy et al., 2007) evaluated optimizing water distribution systems by conducting a case study to minimize the present value of capital and operating costs of the design of the distribution system of an irrigation scheme in New South Wales. The study produced an alternative design that reduced the mass of Polyvinyl Chloride (PVC) pipes used and associated it with a 26.6% reduction in total energy and greenhouse gas emissions. In a similar context, (Thomas, Mantha and Menassa, 2016) presented a model to evaluate the total LCCA of a water transmission pipeline that helps determine the operation, maintenance, and planning of the pipeline over its service life and also identifies its associated environmental impacts at various life cycle phases. More specifically, this paper conducted the LCCA of using an 8” and 24” PVC pipe versus the Ductile Iron (DI) pipe for water distribution and identified that overall, DI pipes turned out to be more cost-effective in the long run and comparatively environmentally friendly.

LCCA has also been applied in fields related to commercial flooring, building integrated photovoltaics, and optimum wall insulation thickness, among others. The sustainable building technical manual shows that the initial procurement cost of commercial buildings accounts for just 10-20% of the total cost, whereas the remaining 80% is due to the O&M and financing (Osso and Gottfried, 1996). D. Kumar et al., 2020 utilized the LCCA approach to determine the optimum thickness of insulation required for different construction materials. The research considered 4 insulation materials and 15 building construction materials to optimize the life-cycle cost that is influenced by decision making variables like thickness and thermal conductivity of the insulation and wall. One of their major outcomes was that materials with high thermal mass and conductivity, such as concrete, have higher LCCA saving potential compared to lightweight wall materials. Hence, from the reviewed studies, it was important to understand that conducting a detailed LCCA of multiple design and material alternatives provided robust feedback on understanding the effect of material alternatives on the overall project from design up to end of service. This understanding can be particularly valuable when examining LCCA's specific applications in building systems and sensor networks.

2.4 LCCA in Building Systems and Sensor Networks

In the domain of sensors and smart building, T. Kumar & Mani, 2017 utilized LCCA as a tool to study the use of occupancy sensors installed in an office building for energy neutrality assessment. This study highlighted the importance of comprehending the influence of any sensor on energy savings to be evaluated from the life-cycle energy framework to understand the overall energy conservation. Using an existing LCCA simulation tool, the study highlighted that occupancy sensors that help in the initial reduction of energy were an ineffective strategy for net energy reduction. The detailed LCCA highlighted the fact that these sensors had high costs and higher environmental impacts due to their packaging contents and the use of rare-earth metals for sensor manufacturing. Moreover, the study also highlighted the fact that the lack of availability of data and standardization of methodology in LCCA studies were some limitations that need to be addressed in this domain (Kumar and Mani, 2017) . Furthermore, (Fang et al., 2020) assessed the life cycle cost of the condition monitoring sensors of a smart distribution room. The data was provided by the Guangzhou power supply bureau and included equipment purchase, operation, failure, recycling, along other life cycle management data. Conducting such a detailed LCCA analysis helped identify that operating cost accounted for 55 to 77% of the total cost, but most of that is accounted towards manual detection is highly influenced by salary growth and inflation rate. This helped confirm that optimizing the inspection process and inspection efficiency improvements can reduce the overall life cycle cost. The analysis also identified methods to help optimize the maintenance costs and reduce the cost of sensor failure.

Table 1 provides an overview of the reviewed studies, highlighting the adopted LCCA approaches. This overview highlights that LCCA has been significantly adopted in a wide range of applications over many years for infrastructure and built environment applications. While some of these studies demonstrated the value of LCCA in evaluating building systems and sensor networks independently, there remains a critical need to adopt this approach in comparing different approaches to buildings' indoor data collection, particularly between fixed sensor networks and emerging robot-based solutions.

Table 1: Overview of Adopted LCCA Approaches and Framework in Different Studies.

Reference	Characteristics/ Limitations
Chan et al. (2008)	Present value analysis for transportation infrastructure evaluation with emphasis on long-term economic
Dandy et al. (2007)	Economic optimization framework incorporating both capital and operational costs for infrastructure
Thomas et al. (2016)	Comprehensive life-cycle framework considering initial investment, operational costs, and environmental
Kumar et al. (2020)	Multi-parameter LCCA optimization framework incorporating material properties and performance
T. Kumar & Mani (2017)	Integration of energy performance metrics into LCCA framework for building automation systems
Fang et al. (2020)	Holistic LCCA approach incorporating procurement, operation, maintenance, and end-of-life costs for

2.5 Need for Probabilistic LCCA and Decision-Friendly Visualization in Building Systems

Most deterministic Life Cycle Cost Analysis (LCCA) approaches typically evaluate the economic feasibility of building projects using static input data, such as net present values, without adequately accounting for uncertainties (Giuseppe, Massi and D'Orazio, 2017). Such uncertainties arise from external factors, including financial risks, market fluctuations, timing of investments, and broader socio-economic considerations. Hence, integrating probabilistic methodologies into the LCCA framework can significantly enhance the robustness of cost assessments (Fregonara, Ferrando and Pattono, 2018). Several recent studies in the domain of building technologies have underscored the importance of addressing these uncertainties. For instance, a study by Fregonara et al. focused on supporting initial design decisions highlighted that deterministic models often neglect variations and risks inherent in building lifecycle management, particularly in early stages of design and technology selection (Fregonara, Ferrando and Pattono, 2018). This work utilized a stochastic approach, employing probabilistic risk analysis and simulation methods to capture the range of possible economic outcomes associated with different design and technology options. The primary goal was to equip investors and decision-makers with clearer insights into cost risks and uncertainties, thus providing greater flexibility and decision-making support. Specifically, this study presented a stochastic LCCA applied to a multifunctional building with a glass façade project located in northern Italy and demonstrated how probabilistic methods revealed significant variabilities in cost outcomes due to flexible input parameters, variations in component service life, and economic and environmental barriers. Importantly, this probabilistic approach provided outcomes that could substantially diverge from deterministic estimates, illustrating that ignoring uncertainties could lead to suboptimal or misinformed investment decisions. Consequently, the authors strongly recommended complementing deterministic analyses with probabilistic methods to improve the accuracy and reliability of life cycle cost evaluations, thereby enhancing decision-makers' confidence and flexibility.

The findings of such studies clearly justify the necessity of moving beyond traditional deterministic LCCA approaches and incorporating probabilistic modeling to better support informed and strategic decision-making in building systems and technology investments. Further emphasizing the significance of addressing uncertainty within LCCA frameworks, another study highlighted that ISO 15686-5:2008 standard ("Buildings and Constructed Assets - Service-Life Planning - Life-Cycle Costing"), explicitly recommends conducting lifecycle cost analyses under conditions of uncertainty or risk (ISO, 2017). According to this standard, statistical methodologies, such as Monte Carlo analysis, should be utilized, explicitly evaluating probabilities at levels of 10%, 50%, and 90%. Recognizing this critical recommendation, Plebankiewicz et al. developed a comprehensive model for estimating the whole-life costs of buildings, explicitly incorporating additional cost factors related to risk and uncertainty, thus enabling investors to compare investment options across multiple economic criteria (Plebankiewicz et al., 2019). The developed model was initially grounded in a fuzzy logic approach, and subsequent stages of model refinement were extensively documented in various related publications. A key objective of their research was to validate the model's structural assumptions by comparing outcomes from the original fuzzy logic-based approach against those obtained from probabilistic analysis methods. In particular, the authors explored the complementary role of probabilistic modeling implemented using Oracle Crystal Ball software, a well-established application for predictive modeling, forecasting, simulation, and optimization in enhancing and validating fuzzy logic assumptions. Their findings clearly demonstrated the significant advantages of probabilistic approaches in explicitly quantifying risks and uncertainties, reinforcing the necessity of integrating these methodologies into LCCA frameworks, as advocated by internationally recognized ISO standards.

Another important aspect, beyond incorporating probabilistic analysis into lifecycle cost assessment, is ensuring that the developed tools are user-friendly and accessible to decision-makers, thereby maximizing their practical utility in real-world case studies. In this context, (Baldoni et al., 2021) developed a specialized software tool for stochastic lifecycle assessment (LCA) and lifecycle costing (LCC) of building energy-efficiency measures. Their study introduced a comprehensive decision-support tool explicitly designed to assist stakeholders during the early design phases of building retrofit interventions. The central objective was to enable users to evaluate the long-term trade-offs between the economic and environmental performance of energy-efficiency projects, while explicitly accounting for uncertainties within input parameters and economic scenarios. Specifically, the authors implemented lifecycle assessment using Monte Carlo methods and modeled lifecycle costing via probabilistic interdependencies among key macroeconomic variables. The major novelty highlighted in their work was the software's intuitive functionality, allowing stakeholders to define uncertainties explicitly, perform robust sensitivity analyses, and explore multidimensional trade-offs systematically. This user-centric approach effectively bridges the gap between complex probabilistic modeling and practical decision-making, enhancing the framework's applicability for both new constructions and retrofitting projects.

Further supporting the importance of intuitive visualization methods, a survey conducted among LCA practitioners found that approximately 70% prefer heatmap-based representations for interpreting and presenting analytical results to broader audiences (Konnovitch and Guglielmi, 2024). Heatmaps intuitively differentiate favorable and unfavorable scenarios through simple color coding, significantly easing stakeholders' interpretation of complex analytical outputs. Such visualization enables decision-makers to quickly grasp how varying input assumptions or alternative design decisions can impact lifecycle costs at a glance, thereby facilitating informed, confident decision-making. Collectively, these studies reinforce the critical need not only for probabilistic approaches such as Monte Carlo simulations to address uncertainties inherent in lifecycle cost analyses but also for intuitive, decision-maker–friendly visualization tools. While these prior studies individually emphasize the value of probabilistic analysis and intuitive visualization, none integrate both aspects comprehensively. In this light, the methodology developed in our research integrates Monte Carlo-based probabilistic modeling, sensitivity analysis, and heatmap visualizations, offering a transparent, robust, and accessible decision-support framework. This integrated approach, aligning closely with practical requirements and real-world decision contexts, is comprehensively detailed in the following section.

3. METHODOLOGY

The objective of the present study was to conduct a comprehensive LCCA to compare the financial feasibility of FWSN and MSR for indoor environmental data collection. The methodology consisted of presenting and discussing the different stages of the developed framework. Following, a detailed elaboration of each stage of the framework was thoroughly explained, which included identifying building characteristics and assumptions, discussing different cost components of the two data collection methods, as well as discussing the LCCA analysis methods, i.e., deterministic and probabilistic measures of NPV. Moreover, the methodology of the sensitivity analysis and heatmap visualization, conducted to investigate the influence of different parameters on the LCCA, was discussed.

Figure 1 shows a business process modelling notation (BPMN) flowchart that summarizes the developed LCCA-based framework. The framework outlines a high-level process for identifying the most cost-effective data collection and monitoring method for an existing building. This process begins by assessing whether the building has any service requirements, such as renovation, building certification, performance monitoring, or maintenance. Once a need is identified, the next step involves determining the specific data requirements and their characteristics. For example, to evaluate the structural performance or energy efficiency of a building, a facility manager may require data on vibration levels, energy consumption patterns, air pressure, airflow rates, and equipment operational status (Burak Gunay, Shen and Newsham, 2019). Following, the LCCA is conducted for the two data collection and monitoring methods and the most economic option is selected. The flowchart provides a framework for systematically defining data needs and evaluating options, laying the foundation for the detailed LCCA comparison between the two methods.

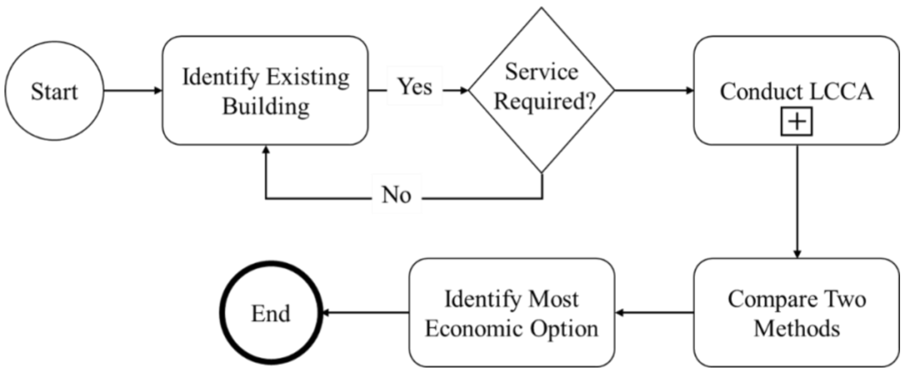


Figure 1: Developed LCCA-based Framework for Building Service Request and Evaluating Financial Viability of Indoor Data Collection Methods.

Figure 2 shows another BPMN flowchart that illustrates the different steps within the LCCA sub-process in the general framework. This flowchart outlines a structured methodology for conducting an LCCA to compare two methods for data collection and monitoring in buildings. While this methodology is applied in this paper specifically to evaluate FWSN versus MSR, it is versatile and can be adapted to compare any two approaches or technologies in similar contexts. The process begins by defining building characteristics and assumptions, followed by identifying all necessary cost components for both data collection approaches. Using these inputs, NPV calculations are performed for both solutions through a deterministic approach, followed by probabilistic Monte Carlo simulations to evaluate cost variations under different scenarios. An iterative mechanism is incorporated to enable repeated comparisons, if adjustments to input parameters or configurations are necessary. The results are then evaluated and validated by conducting sensitivity analysis and heatmap visualizations, which highlight the cost-effectiveness of the solutions across different configurations. By thoroughly analyzing data characteristics, such as collection frequency, quality, and location-specific sensitivity, this methodology ensures a comprehensive comparison.

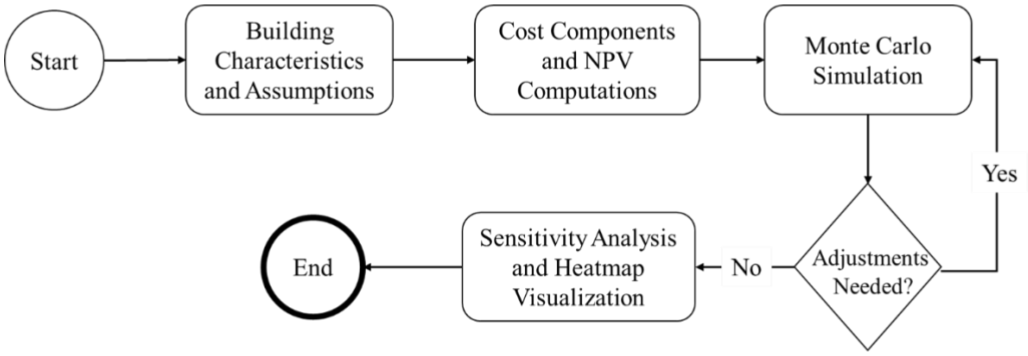


Figure 2: Flowchart of Stages Involved in the LCCA Sub-process.

4. BUILDING CHARACTERISTICS AND ASSUMPTIONS

The first step in the developed LCCA methodology involved defining the key building parameters and assumptions that influence cost and performance evaluation. These parameters are critical for accurately estimating the total costs and ensuring the reliability of data collection models. For instance, building floor space serves as a fundamental metric, as it directly impacts the cost estimation, particularly in systems where expenses are often expressed on a per-square-foot basis (Fuller and Petersen, 1995; Fissore et al., 2024). Data quality and reliability are governed by sensor density and the temporal intervals of data collection. For example, denser sensor placement and more frequent sampling, both improve detection of spatial variation and dynamic changes in common metrics such as CO2, temperature, and humidity (Saini, Dutta and Marques, 2020; Corona et al., 2024; Fissore et al., 2024). Hence, sensor distribution and data collection intervals were prioritized in this methodology, reflecting norms outlined in contemporary sensor deployment studies. The discount rate, meanwhile, remains a foundational aspect of financial evaluation, as validated by seminal and current LCCA literature (Fuller and Petersen, 1995; Kneifel and Webb, 2022). Therefore, these parameters, namely indoor floor space, sensor density, data collection intervals, and discount rate, were selected as critical for constructing a robust, reliable framework to compare life cycle costs and performance across distinct data collection models.

5. COST COMPONENTS AND NPV COMPUTATIONS

To accurately conduct an LCCA of a facility, it is necessary to identify different cost components namely, initial, O&M, replacement, and disposal costs consistent with the definition provided by the National Institute of Standards and Technology (NIST) Handbook 135 (2022), which describes Life Cycle Cost (LCC) as "the total discounted dollar cost of owning, operating, maintaining, and disposing of a building or a building system" over a designated period of time (Kneifel and Webb, 2022). This approach allows for a thorough comparison of the financial implications of different data collection and monitoring methods, ultimately guiding decision-makers in selecting the most economical and efficient solution. The detailed cost components for each data collection and monitoring method, i.e., FWSN and MSR, are discussed in the subsequent subsections. After obtaining the different cost components of both methods, the NPV was computed, which involved a detailed examination of all costs incurred throughout the facility's life cycle. The deterministic computation of NPV for each cost component was carried out as follows, with the help of Eq. (1) and Eq. (2) shown below, consistent with the life cycle costing practices (Fuller and Petersen, 1995; Sieglinde Fuller, 2010).

$$NPV = PA * (d + f) * \frac{(1 - \left(\frac{1+f}{1+d}\right)^n)}{(d - f)} \tag{1}$$

$$NPV = \sum_{i=1}^{i=k<\frac{n}{M}} \frac{PF*(1+f)^{\left\lfloor\frac{i*M}{12}\right\rfloor}*\left(1+\frac{f}{12}*((i*M)mod12)\right)}{(1+d)^{\left\lfloor\frac{i*M}{12}\right\rfloor}*\left(1+\frac{d}{12}*((i*M)mod12)\right)} \tag{2}$$

Where *PA* represents annually recurring costs estimated at the base year, *d* is the discount rate, *f* is the inflation rate, *n* is the study period, *PF* is the future cash amounts occurring at the end-of-life stage valued at the base year, *M* is the lifespan in months, and k is an integer denoting the frequency of cost occurrences. The importance of calculating the NPV lies in evaluating the costs at a similar scale, i.e., at the base year. This approach ensured that all costs are brought to a comparable baseline, allowing for accurate and fair comparison between the FWSN and MSR data collection and monitoring approaches. Once the NPV of all cost components is computed, the total cost of each data collection method can be computed as shown in Eq. (3) below.

$$LCCA = NPV_{IC} + NPV_{O\&M} + NPV_{RC} + NPV_{DC} \tag{3}$$

Where *IC* is the initial costs, while $NPV_{O\&M}$, NPV_{RC}, and NPV_{DC} are the NPVs of O&M, replacement, and disposal costs, respectively. It should be noted that for initial costs, the NPV was equivalent to the actual costs, as these costs are already incurred in the base year. Also, disposal costs represented the only positive cashflow in the LCCA computation.

5.1 FWSN

FWSNs consist of sensors strategically installed at various locations within a building to collect critical information for building automation systems. These sensors are centrally controlled through a server, enabling efficient data acquisition and management to support automation processes. The LCCA of FWSN involves evaluating its different cost components, summarized in Table 2, incurred throughout its lifespan. The initial costs of FWSNs encompass several key elements, primary among these are sensor procurement and installation costs (including tools and equipment necessary for setup), as well as labor charges (Fuller, 2005). The total sensor cost, as expressed in Eq. (4), is usually determined during the installation stage by estimating the number of sensors required. This was calculated by dividing the total floor area (in square feet) by the coverage density of each sensor (sqft/sensor). Once the sensor quantity was determined, the total procurement cost was computed accordingly. It should be noted that initial costs also include infrastructure components such as gateway devices and network setup. However, these costs were excluded as they were considered constant factors necessary for both FWSN and MSR systems, which do not affect the relative LCCA comparison. Moreover, labor costs for installation were calculated using Eq. (5), which considered the proportional relationship between total floor area and installation duration. The calculation applies a standard industry “all-in” daily labor rate widely used in construction cost estimation tools that includes both direct wages and indirect costs such as payroll taxes, insurance, equipment usage, and safety compliance (Melkonyan & Muradyan, 2025). The authors considered daily rates more appropriate than hourly rates in this context, as the modeled installation tasks are assumed to span full working days and would typically be executed by third-party contractors under lump-sum or daily agreements. For simplicity, the number of installation days was assumed to scale with floor area, with the labor quantity remaining constant. However, industry standards also recognize that in larger or more complex projects, additional installers are often deployed in parallel rather than extending a single team’s duration (NenPower, 2024). While this study does not explicitly model installation complexity, the assumption is informed by industry guidance, which indicates that factors such as sensor location (e.g., ground level versus high-rise), limited access, and safety requirements typically increase labor duration and associated costs (NenPower, 2024). These aspects are noted as limitations of the present model and are identified as areas for future refinement.

$$Sensors\ cost = (Cost\ of\ each\ sensor) * ((Floor\ Space)/(Space\ Range\ Density)) \tag{4}$$

$$Labor\ cost = daily\ labor\ wages * total\ days * no.of\ labor \quad (5)$$

Furthermore, operational costs for FWSN were primarily driven by the battery-powered energy consumption of the sensors. According to Zachary Denning (2016), typical building monitoring systems allocate 60%-70% of their O&M expenses to energy usage, while the remaining 30%-40% is attributed to maintenance activities. Given that the total number of sensors in the building remained constant over time, the O&M costs were identical for both deterministic and probabilistic computations in the LCCA methodology. On the other hand, replacement costs included expenses for purchasing new sensors and reinstallation when needed. The replacement cycle is primarily driven by sensor battery life and technology obsolescence rather than mechanical failure. Finally, disposal costs for FWSN systems were excluded from the analysis, as these sensors generally lack salvage value at the end of their life cycle, are small in size, and currently fall outside the scope of any specific e-waste disposal regulations set by the Government of India (A R, 2019; BV Recyclers, 2016).

Table 2: Cost Components of FWSN for Data Collection and Monitoring.

Cost Component	NPV Computation	Contributing Parameters
Initial Cost	-	• Sensors' procurement and installation • Labour charges
O&M Costs	Eq. (1)	• Power consumption charges • Periodic repair and service charges
Replacement Cost	Eq. (2)	• Re-procurement of sensors • Re-installation charges

5.2 MSR

A mobile robotic platform for sensor networks comprises a robot equipped with on-board components such as a Netbook, iCreate Base, RGB camera, and sensors, which navigate the floor space using stationary markers installed at strategic locations. These robots traverse the entire floor area, collecting data at designated sites through a built-in navigation framework (Mantha et al., 2020). The initial costs included the main cost-incurring parameters in an MSR-based data collection system, namely procurement of robots and their on-board sensors, as well as additional equipment costs encompassing the Netbook, iCreate Base, and RGB camera. These components enable efficient data collection and storage during operation.

To estimate the number of robots required for a given floor space, the approach proposed by Mantha et al. (2020) was adopted in the present study (Mantha et al., 2020). Their study highlighted that a typical floor plan of 3000 sqft necessitated three robots and three depots to complete ambient data collection tasks. Each depot served as a base location for the robots, functioning as a start/end point or a charging station. The time taken by each robot to complete a tour and return to its respective depot, termed "tour time," was determined by the distance traversed and the robot's velocity. Table 3 provides the adopted tour lengths and times for each robot starting from its designated depot at a velocity of 0.22 m/s. If the required data collection period is denoted as T, the number of robots required at each depot i can be calculated as t_i/T, where t_i represents the tour time for the robot. This approach ensures efficient deployment of robots based on the specific requirements of the floor plan. The method described by Mantha et al. (2020) offered a practical framework for determining the optimal number of robots needed for effective data collection in an MSR network. It enables scalable deployment and efficient resource utilization, tailored to varying floor plans and operational needs.

Table 3: Base Case Values for Each MSR Tour Length and Time (adopted from Mantha et al. (2020)).

Depot #1.	Depot #2	Depot #3
Length of tour = 4m	Length of tour = 3.4m	Length of tour = 76.1m
Tour time (t_1) = 4/0.22 = 0.3min	Tour time (t_2) = 3.4/0.22 = 0.26min	Tour time (t_3) = 76.1/0.22 = 5.76min

Moreover, the estimation of the total number of robots required for deployment in an indoor environment is based on the principle of proportionality. Given that area (A) is proportional to the square of length, the distance (d_0) covered by a robot for a specific area can be proportionally scaled. For area A, the relationship to the distance d_0 traversed by a robot over a reference area of 3000 sqft is represented by Eq. (6). At a constant robot speed, distance and time are directly proportional. This relationship is expressed in Eq. (7), where N_i is the number of robots required at the i^{th} depot, t_i is the tour time for a robot at that depot, and T is the total time period allocated for data collection.

To maintain continuity in data collection throughout the indoor building, the deployment strategy must account for the time robots spend charging. As a result, the total number of robots required was effectively doubled to ensure uninterrupted operation. The final estimate of the total number of robots to be deployed was calculated using Eq. (8). This approach ensured adequate robot availability to achieve seamless data collection while accommodating operational constraints such as charging cycles.

$$Distance\ covered = d_0 \sqrt{(Area(sqft))/3000\ sqft} \tag{6}$$

$$N_i = \lceil t_i/T * \sqrt{(A/3000)} \rceil \tag{7}$$

$$Total\ Robots = 2 \times \sum_{i=1}^{3} N_i \tag{8}$$

In addition to initial costs, operational costs for an MSR platform were primarily driven by power consumption charges for both the robots and their onboard sensors. Additionally, maintenance costs included service and handling charges associated with the robotic system. This study assumed that a single employee is sufficient to oversee the operation and maintenance of the robots and sensors, simplifying the management requirements. Replacement costs, which occur at the end of the operational lifespan of the robots and on-board sensors, include expenses for re-purchasing and re-installation of new equipment upon obsolescence of previously employed robots and/or their on-board sensors. Moreover, disposal costs for the MSR-based system represented the resale value of robots, which were estimated based on market trends and conditions, providing a comprehensive evaluation of end-of-life expenses associated with the platform. This integrated approach ensured an accurate and practical analysis of the operational and replacement costs within the LCCA framework. Table 4 summarizes the different cost components of MSR for data collection and monitoring.

Table 4: Cost Components of MSR for Data Collection and Monitoring.

Cost Component	NPV Computation	Contributing Parameters
Initial Cost	-	• Procurement of robots and on-board sensors • Procurement of additional equipment
O&M Costs	Eq. (1)	• Power consumption charges • Service and handling charges
Replacement Cost	Eq. (2)	• Re-procurement of robots and on-board sensors • Re-installation charges
Disposal Cost	Eq. (2)	• Re-sale value of robots

6. MONTE CARLO SIMULATIONS

In addition to the deterministic approach for estimating the NPVs of FWSN and MSR, a probabilistic method was integrated into the LCCA framework to account for uncertainties in the input data, enhancing its alignment with real-world applications. This approach incorporates stochastic variations, such as deviations in the lifespan of sensors and robots, which are often observed in practice. For example, while a batch of 100 sensors might have a nominal lifespan of 10 years, individual sensors could vary, lasting between 9 and 11 years. To model this uncertainty effectively, Monte Carlo simulation was employed, which is a well-established technique for generating robust probabilistic outcomes across various disciplines.

Monte Carlo methods simulate random events within a computational model, iterating thousands of times to produce a distribution of possible outcomes rather than a single fixed value (Kroese et al., 2014). When applied in LCCA, the NPV is no longer a constant but a distribution, reflecting the variability and uncertainty inherent in the inputs. This probabilistic approach introduced a reliability metric to validate the results of the deterministic model. In the present analysis, a reliability percentage exceeding 90% was adopted as the decision criterion, following standard LCCA practices that use confidence or reliability thresholds between 85–9(Morán-Zabala & Cogollo-Flórez, 2024)n-Zabala & Cogollo-Flórez, 2024). Moreover, the simulations utilized an assumed triangular distribution for the input variables, as illustrated in Figure 3, to generate possible values for each scenario which is widely used in project risk and cost simulations (Barreras, 2011; Sihombing and Saputra, 2025). The ±10% variability range was selected in line with precedent from cost uncertainty modeling in infrastructure studies and government guidance (Environmental Management Consolidated Business Center (EMCBC) Office of Cost Estimating (OCE), 2023). For each iteration, a corresponding NPV was calculated, and the process was repeated 10,000 times to ensure statistically significant results a number determined through convergence testing and consistent with prior probabilistic cost modeling studies (Heijungs, 2020). This comprehensive approach enabled informed decision-making by incorporating both deterministic and probabilistic evaluations.

Triangular Distribution Random Number

Lower Range = Mode-Minimum

Higher Range = Maximum-Mode

Total Range = Maximum-Minimum

Cumulative Probability = Rand()

If CumulativeProbability < (LowerRange/TotalRange) then

RandomTriangular = Minimum+sqrt(CumulativeProbability*LowerRange*TotalRange)

Else

RandomTriangular = Maximum-sqrt((1-CumulativeProbability)*HigherRange*TotalRange)

Figure 3: Monte Carlo Simulation's Triangular Distribution for Input Variables.

In the case of calculating the NPV for replacement costs, i.e., NPV_{RC}; these costs are directly related to the lifespan of sensors and/or robots in both FWSN and MSR approaches. To account for uncertainty in sensor life, the probabilistic model was employed, assuming the lifespan follows a triangular distribution with a ±10% variation around the most probable value. In contrast, in the deterministic model, the most probable value was uniformly adopted as the expected lifespan. Figures 4a and 4b illustrate the conducted Monte Carlo Simulation for LCCA of FWSN and MSR data collection approaches, respectively.

7. SENSITIVITY ANALYSIS AND HEATMAP VISUALIZATION

In the present study, sensitivity analysis and heatmap visualization were employed to evaluate the conducted LCCA of different sensor network configurations. Sensitivity analysis was utilized to examine the influence of key parameters, namely floor space, discount rate, sensor density, and data collection intervals, on the NPV of data collection systems (C. Lee & Lee, 2017; Marenjak & Krstić, 2010; Mobaraki et al., 2021).This analysis enabled the identification of parameter dependencies and thresholds, highlighting critical breakeven points that aid in economic feasibility assessments. By systematically varying these parameters, the sensitivity analysis provided a deterministic understanding of how each factor affects cost outcomes, offering valuable insights into the interdependence among variables.

Moreover, to enhance the robustness of the evaluation, heatmap visualization was incorporated as a complementary probabilistic approach. The limitation of performing sensitivity analysis independently lies in its deterministic framework, which fails to account for variability and uncertainty in outcomes across different parameter modifications (Razavi et al., 2021). However, heatmaps can account for uncertainties and variability in parameter values, enabling the simultaneous evaluation of multiple variables and their impact on the LCCA (Zhao, Seppänen and Peltokorpi, 2020). Heatmaps presented a matrix-based representation of data, illustrating the probability that one sensor network configuration would be more economical than another under varying conditions (Key, 2012). This probabilistic framework provided a clearer understanding of trends, transitions, and patterns, thereby offering practical insights into optimal sensor network strategies for specific scenarios. The combination of sensitivity analysis and heatmap visualization formed a comprehensive framework for LCCA evaluation in this study. While sensitivity analysis provided foundational insights into parameter impacts, heatmaps addressed the stochastic nature of real-world conditions, enhancing the reliability and applicability of the findings. This combined approach ensured a detailed and nuanced assessment, supporting informed decision-making for facility planning and management.

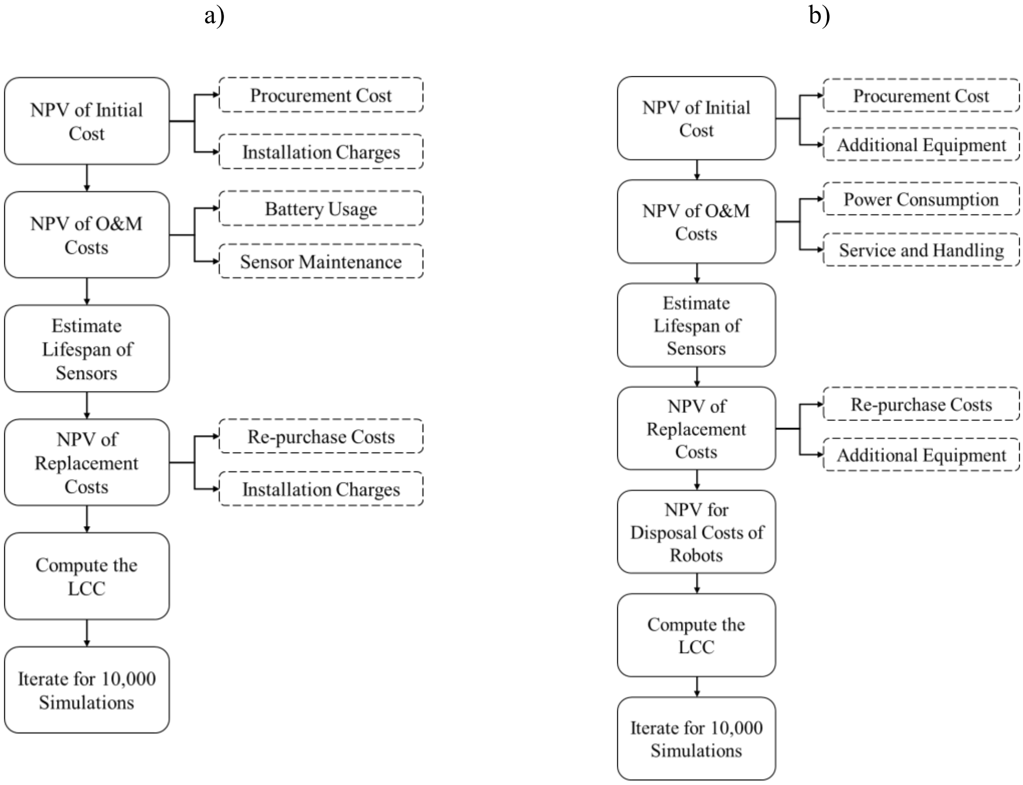


Figure 4: Monte Carlo Simulation Framework for the LCCA of a) FWSN and b) MSR Data Collection Approaches.

8. RESULTS AND DISCUSSION: CASE STUDY

The main objective of the present study was to develop an LCCA framework to evaluate and compare the financial feasibility of FWSN and MSR systems for indoor environmental data collection. A case study was conducted in the present paper to validate the developed methodology, where three distinct scenarios were analyzed, i.e., small, medium, and large commercial complexes, to demonstrate the application of the methodology across varying building sizes. The results discussed included analyzing the LCCA of each system for the three established scenarios. The LCCA was analyzed using both deterministic NPV calculations and Monte Carlo simulations to assess the reliability of the findings under varying conditions. Following, results of the conducted sensitivity analysis and generated heatmap visualizations for each scenario were discussed.

In the selected case study, a building lifespan of 50 years was adopted, consistent with standard lifecycle assessment practices such as those recommended by the U.S. General Services Administration (GSA) and the University of California LCCA guidelines (University of California, 2023; U.S. GSA, 2025), with the case study location set in Mumbai, India. The total floor areas considered were 60,000 sqft, 125,000 sqft, and 250,000 sqft for the small, medium, and large complexes, respectively. Although there isn't a standard area based classification, national building code (NBC)'s categorization of low, mid, and high rise buildings closely aligns with the small medium and large buildings (L&T Realty, 2024; Ramamirtham, 2025). Moreover, recent commercial developments like the World Trade Center (WTC) Pune feature office towers with built-up areas of approximately 370,000 square feet (World Trade Center Pune, 2025). All present-value costs associated with the selected study area are detailed in Table 5.

Table 5: Different Costs of FWSN and MSR Components in the Study Area.

No.	Cost Component	Value (₹)	References
1	Cost of fixed sensor	6,150	(HOBO, 2024)
2	Cost of mobile-based indoor robots	41,175	(Robotis, 2024)
3	Cost of onboard sensors	8,911	(CO2Meter.com, 2015)
4	Annual charges for sensor maintenance	40% of O&M	(Zachary Denning, 2016)
5	Monthly charges for robot maintenance	30,000	(Payscale, 2024)
6	Re-sale value of robots	10% of initial cost	(Robots Done Right, 2024)
7	Cost of additional equipment on robot	100,000	(Lenovo India, 2024)

Moreover, Table 6 summarizes the different input parameters utilized for NPV computations, as well as the brands of employed sensors and mobile-based indoor robots. The analysis incorporated a discount rate of 7.5% and an inflation rate of 4.3%, based on values reported in the literature (Fang et al., 2020; O'Neill, 2024). Furthermore, space range densities of different commercial sensors range significantly from as low as 100 sqft/sensor for small areas up to more than a 1,000 sqft/sensor for more advanced sensors utilized in larger areas (VergeSense, 2022; Lutron, 2014). In this study, a space range density of 200 sqft/sensor was assumed for the FWSN approach, a value closer to commercial values of sensors utilized in indoor spaces with similar areas, and electricity costs were calculated using a rate of Rs. 10/unit, reflecting commercial rates in Mumbai (Adani Electricity, 2024). Additionally, labor charges for setting up the facility were based on the Government of India's minimum daily wage rate of Rs. 450/day (Chief Labour Commissioner, 2024).

Table 6: Input Variables Utilized in NPV Computations and Description of Employed Sensors and Mobile-based Robots.

No.	Description	Input Data	References
1	Discount rate	7.5%	(Fang et al., 2020)
2	Space density of fixed sensors	200sqft/sensor	(VergeSense, 2022; Lutron, 2014)
3	Inflation rate	4.3%	(O'Neill, 2024)
4	Wall-mounted sensor	HOBO Temperature Logger UX100-001	(HOBO, 2024)
5	Mobile-based indoor robot	Turtlebot3 Burger	(Robotis, 2024)
6	Robot's on-board sensor	CozIR-A 2000ppm CO2+ RH/T sensor	(CO2Meter.com, 2015)
7	Time period of robotic data collection	30min/reading	(Mantha et al., 2020)
8	Electricity charges per unit	10 Rs/unit	(Adani Electricity, 2024)
9	Labour charges for facility set-up	450 Rs/day	(Chief Labour Commissioner, 2024)

Operational costs were calculated using a 9V lithium battery for the fixed wireless sensors and electricity charges for recharging robot batteries. The analysis assumed an employee salary growth rate equal to the inflation rate. The expected lifespan values for sensors, robots, and on-board sensors were taken as 10, 7, and 15 years, respectively, based on typical market data (CO2Meter.com, 2015; HOBO, 2024; Robotis, 2024). As a baseline, the data collection interval was set to 30 minutes per reading, as suggested in previous studies (Mantha et al., 2020). However, the developed methodology allows building managers to customize these inputs based on specific requirements. The results of this case study aim to provide valuable insights into the comparative LCCA performance of FWSN and MSR systems under different building conditions, supporting informed decision-making for building automation strategies.

8.1 LCCA Results

The NPV of both FWSN and MSR systems was computed using deterministic and probabilistic methods for small, medium, and large complexes. Figures 5-7 show the cumulative annual NPVs and Monte Carlo simulations results for each complex size. For the small complex with a floor space of 60,000 sqft, deterministic calculations indicated that the FWSN was more cost-effective than MSR data collection, as determined by NPV analysis. The total NPV after a 50-year operational lifespan was around 35 and 90 million INR for the FWSN and MSR systems, respectively. Additionally, Monte Carlo simulations corroborated these results, yielding a 100% reliability index, which confirmed that the deterministic conclusion holds true for the given input values. Similarly, for a medium-sized floor space of 125,000 sqft, deterministic NPV calculations also showed that the FWSN system was more feasible with a total NPV of around 70 million INR compared to about 100 million INR for the MSR system. However, for this scenario, Monte Carlo simulations revealed a low reliability index of 45.3%, indicating significant uncertainty in the results. This observation suggested that the chosen input values for this scenario were close to the breakeven point, where slight variations in the parameters could reverse the conclusion. On the other hand, in a large complex with a floor space of 250,000 sqft, deterministic calculations showed that MSR data collection was more cost-effective than FWSN with total NPVs of around 90 and 140 million Rs, respectively. This conclusion was further supported by Monte Carlo simulations, which provided a 100% reliability index. The results from the three scenarios highlight the importance of conducting sensitivity analysis to better understand the influence of major parameters on the LCCA outcomes.

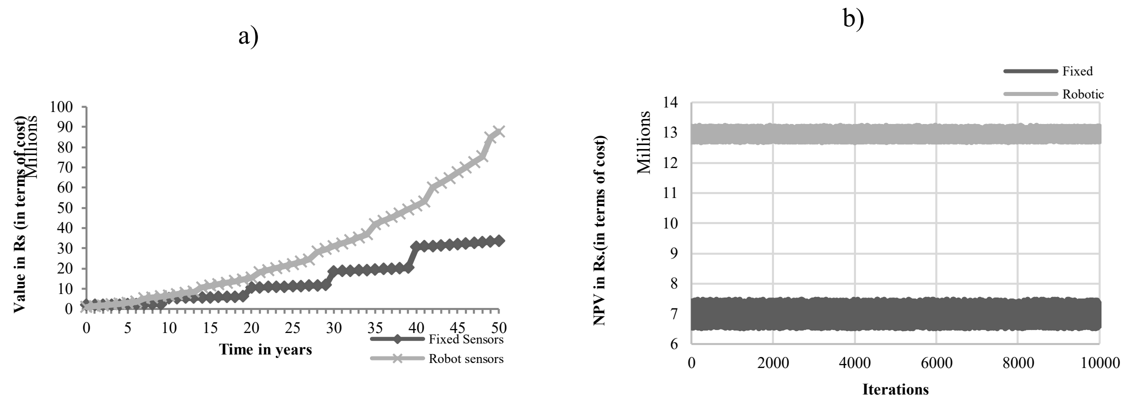


Figure 5: LCCA Results for the Small Commercial Complex Scenario: a) Cumulative Annual NPV and b) Monte Carlo Simulations.

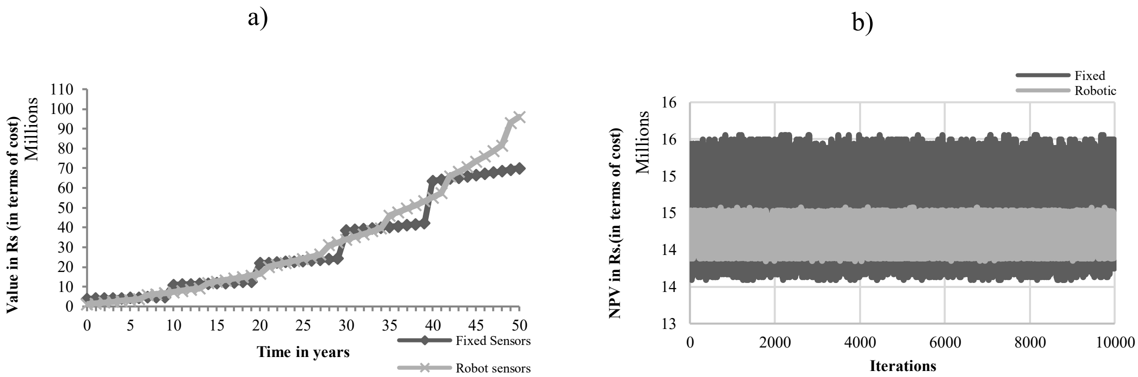


Figure 6: LCCA Results for the Medium Commercial Complex Scenario: a) Cumulative Annual NPV and b) Monte Carlo Simulations.

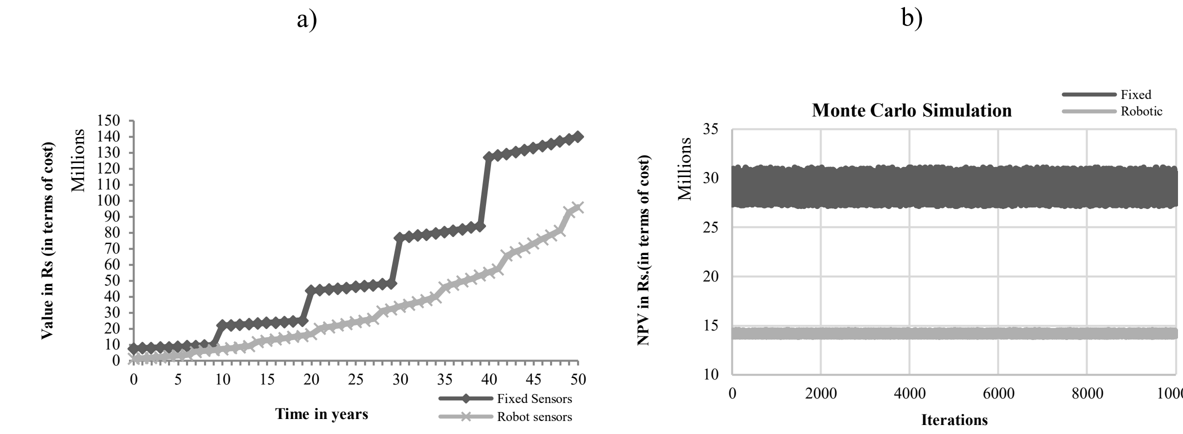


Figure 7: LCCA Results for the Large Commercial Complex Scenario: a) Cumulative Annual NPV and b) Monte Carlo Simulations.

8.2 Sensitivity Analysis

Following the evaluation of computed NPVs, sensitivity analysis was conducted to examine the influence of key parameters on the NPV for both FWSN and MSR indoor data collection methods. As previously mentioned, sensitivity analysis was conducted on the floor space, discount rate, space range density, and time period of data collection, by evaluating and analyzing the impact of varying their values on the obtained NPV. Figures 8-11 show the change in total NPV due to variations in each of the aforementioned parameters for both FWSN and MSR systems for each complex size scenario. The results of sensitivity analysis on discount rate (Figure 8) showed that the NPV exhibited a parabolic decrease as the discount rate increased from 1% to 10%. Additionally, the difference between the NPVs of FWSN and MSR data collection systems diminished with an increasing discount rate, highlighted by a larger gap at smaller discount rates between the NPV of FWSN and MSR compared to the gaps at higher discount rates. However, in scenario 2, the initial gap was reduced between the two systems and the curves intersected at a discount rate of 6%, indicating a breakeven point for the two alternatives. This suggests that a higher discount rate reduced the economic viability of long-term investments for FWSNs.

The relationship between NPV and floor space (Figure 9) revealed that the FWSN was more feasible for smaller areas, but its NPV increased exponentially as the area increased. In contrast, the NPV of MSR increased gradually, resulting in a breakeven point with the FWSN system at a floor space area of around 125,000 sqft. Beyond this threshold, the MSR system outperformed the fixed network, showing larger gaps between the NPV of both systems at larger floor space areas. This observation aligns with the fact that the number of robots is proportional to the square root of the area (Eq. 7), whereas the number of sensors is directly proportional to the area (Eq. 4). On the other hand, the impact on NPV due to varying the time period of data collection (Figure 10) showed that the FWSN remained constant in each scenario because wall-mounted sensors can typically adjust their sensing frequency without incurring additional costs. However, for MSR-based data collection, the NPV decreased rapidly at first and then declined more gradually. The initial steep decrease was attributed to a significant percentage reduction in the number of robots required. For example, based on Eqs. 6-8, the number of robots for a 1-minute reading interval is 60, which drops to 30 for a 2-minute interval (a 50% reduction). As the time interval increases further, the percentage change becomes smaller, leading to a less steep curve. A breakeven point was observed in scenario 2 at a time period for data collection of 20 minutes, while the breakeven point in scenario 3 was observed at 5 minutes.

Furthermore, for space range density (Figure 11), the MSR system showed a constant NPV because robots are capable of traversing the entire floor plan regardless of sensor density. In contrast, the NPV for FWSN decreased rapidly at first and then flattened out. This trend was driven by the percentage change in the number of sensors required. For example, for densities of 50, 100, and 150 sqft/sensor, the number of sensors required is 1,200, 600, and 400, respectively, resulting in percentage reductions of 50% and 33.33%. This led to an initially steep decline in the NPV curve, which became more gradual at higher densities. However, the gaps between the NPVs of FWSN and MSR systems were increased as the complex size increased, due to the increased NPV of FWSN at lower space range densities utilized in larger areas. Also, breakeven points were observed at values of 100, 200, and 400 sqft/sensor of space range density for scenario 1, 2, and 3, respectively. Overall, the conducted sensitivity analysis results illustrated the impacts of altering different parameters on the appropriate selection of indoor data collection methods from the financial perspective. However, in almost all instances, MSR-based data collection systems were more feasible for larger complexes, which was aligned with the obtained LCCA results. These findings provide critical guidance for selecting the most cost-effective data collection strategy based on the specific conditions and parameters of a project.

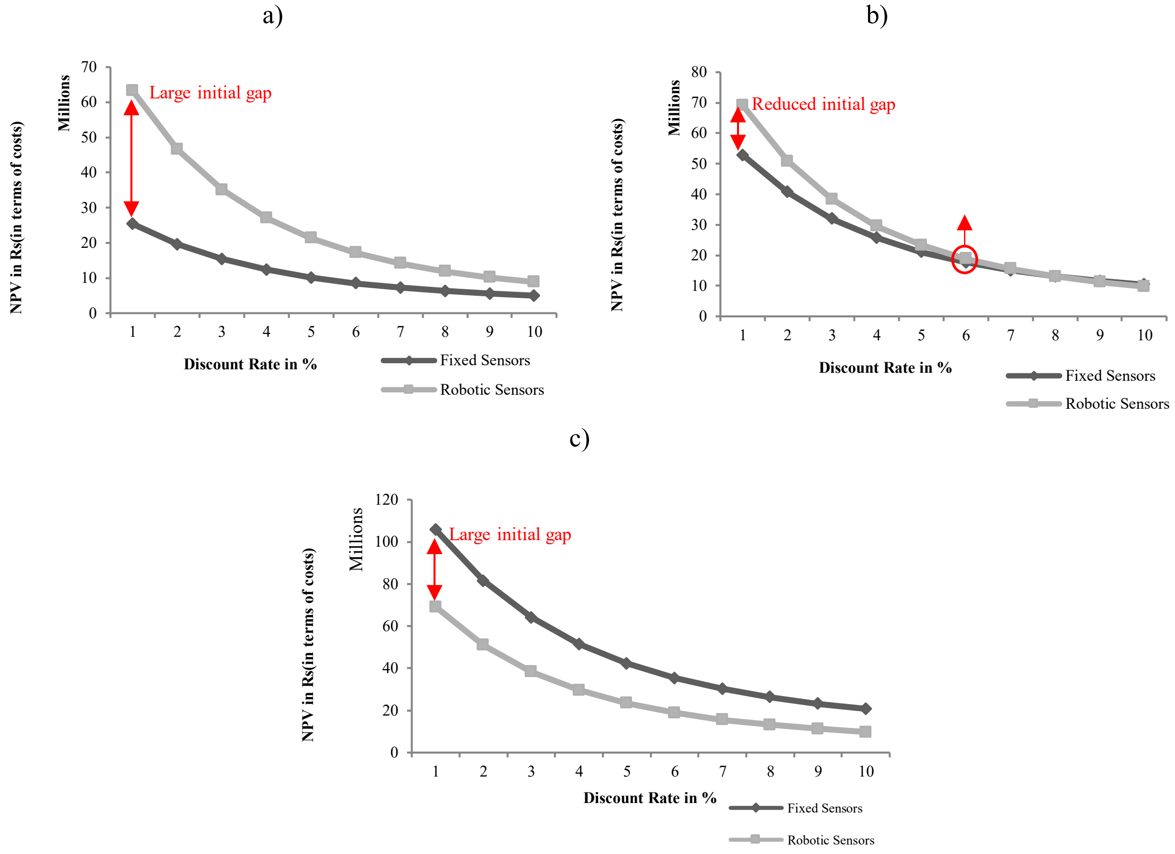
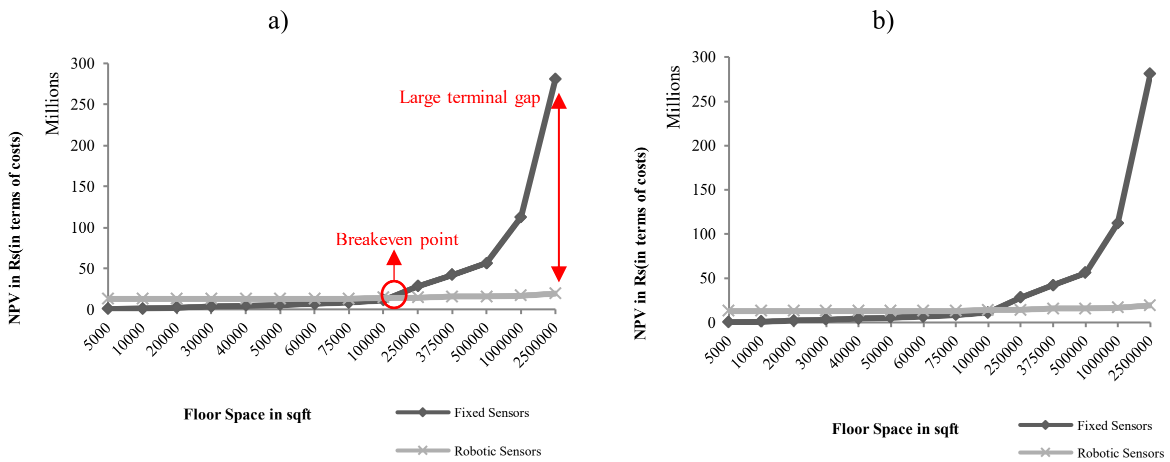


Figure 8: Impact of Discount Rate on the NPV of FWSN and MSR Data Collection Systems: a) Small, b) Medium, and c) Large Complex Scenarios.



c)

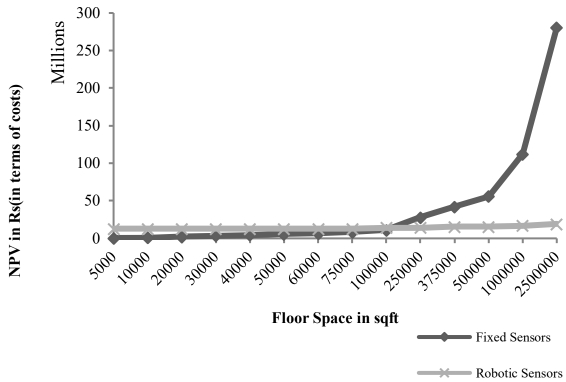


Figure 9: Impact of Floor Space on the NPV of FWSN and MSR Data Collection Systems: a) Small, b) Medium, and c) Large Complex Scenario.

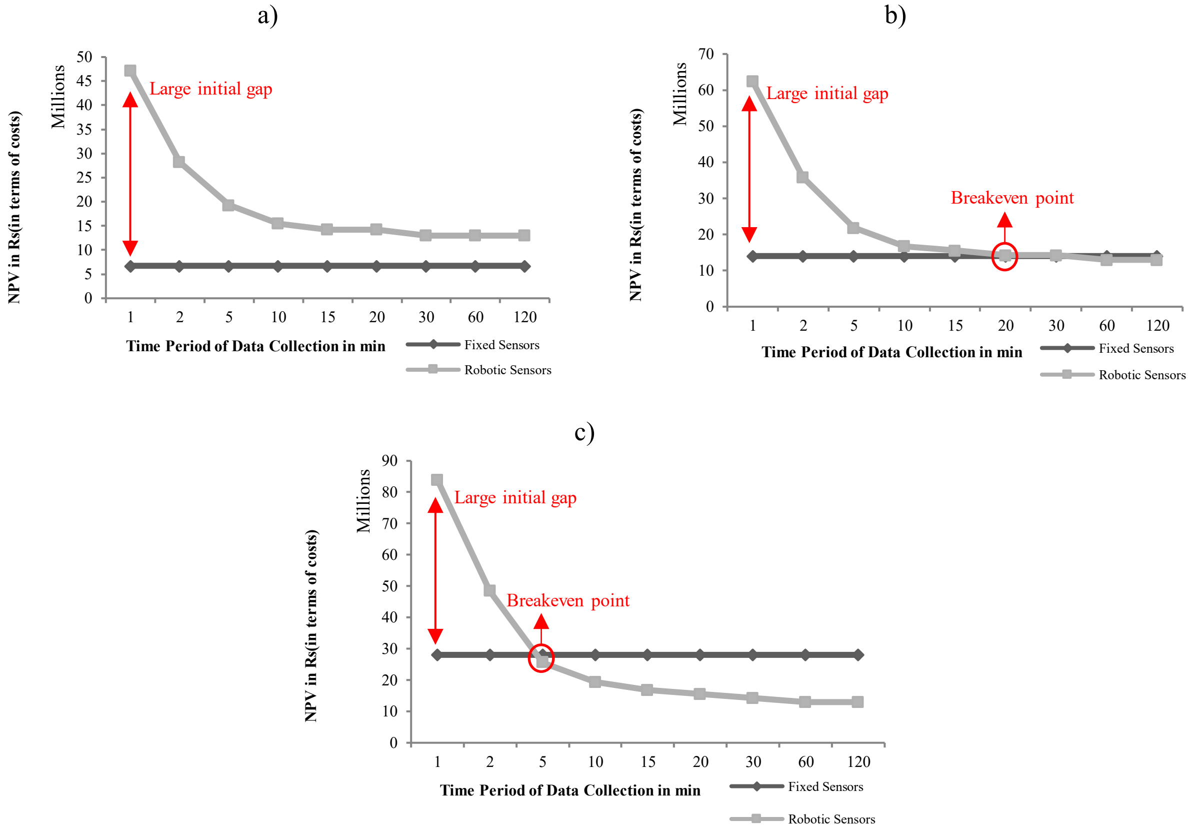


Figure 10: Impact of the Time Period of Data Collection on the NPV of FWSN and MSR Data Collection Systems: a) Small, b) Medium, and c) Large Complex Scenarios.

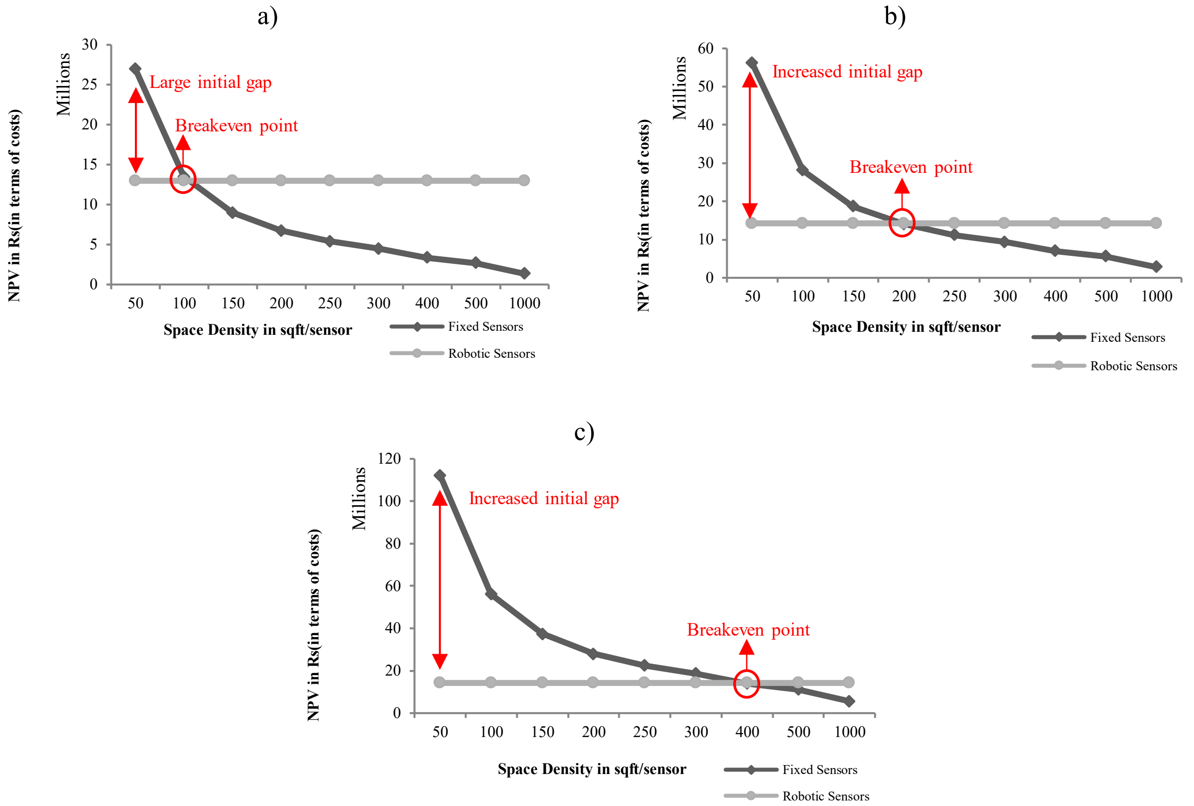


Figure 11: Impact of Space Range Density of fixed sensors on the NPV of FWSN and MSR Data Collection Systems: a) Small, b) Medium, and c) Large Complex Scenarios.

8.3 Heatmap Visualization

In addition to the conducted sensitivity analysis, heatmap visualization was conducted to identify the most economical data collection strategy across a range of input characteristics. Heatmaps were generated in this study to visualize the influence of key parameters on the probability of MSR-based data collection system being more cost-effective than FWSN-based data collection. This approach was adopted to facilitate a clearer understanding of parameter interactions and simplify decision-making processes for facility managers. For the selected case study, heatmaps were generated by varying floor space (sqft) and space range density (sqft/sensor) along the x and y axes, respectively. The time period of data collection was systematically varied from 1 to 60 minutes, i.e., 1, 5, 10, 15, 20, 30, and 60 minute-intervals, based on practical considerations, while the discount rate was fixed at 7.5%. Other input values were not changed and remained constant, and each heat map was developed using 10,000 iterations to ensure statistical reliability. Figure 12 shows the heatmaps generated for each time period of data collection scenario.

Based on the generated heatmaps, some key findings were observed. For instance, the heatmaps demonstrated that, for a given floor space and space range density, the probability of MSR data collection being more economical increased as the time period of data collection extended. For example, for a floor space of 160 sqft and space range density of 200 sqft/sensor, the probability of MSR data collection being more financially feasible was 0, 0, 64, and 100% for 1, 5, 10, and 15-60 minutes time periods, respectively. This trend highlighted the efficiency of robotic systems in scenarios requiring less frequent data readings. Additionally, for smaller space range densities (up to 150 sqft/sensor) and lower floor spaces, an abrupt transition was observed in the probability of robotic data collection being cheaper. This was attributed to the significant percentage change in the number of sensors required, which directly impacted on the costs incurred. As the space range density increased, these abrupt transitions diminished, resulting in smoother heat map gradients for higher values. Moreover, the heatmaps also revealed regions where neither alternative had a clear economic advantage, with probabilities ranging from 25% to 75%. These regions highlighted conditions under which further analysis or additional parameters may be needed to make an informed decision.

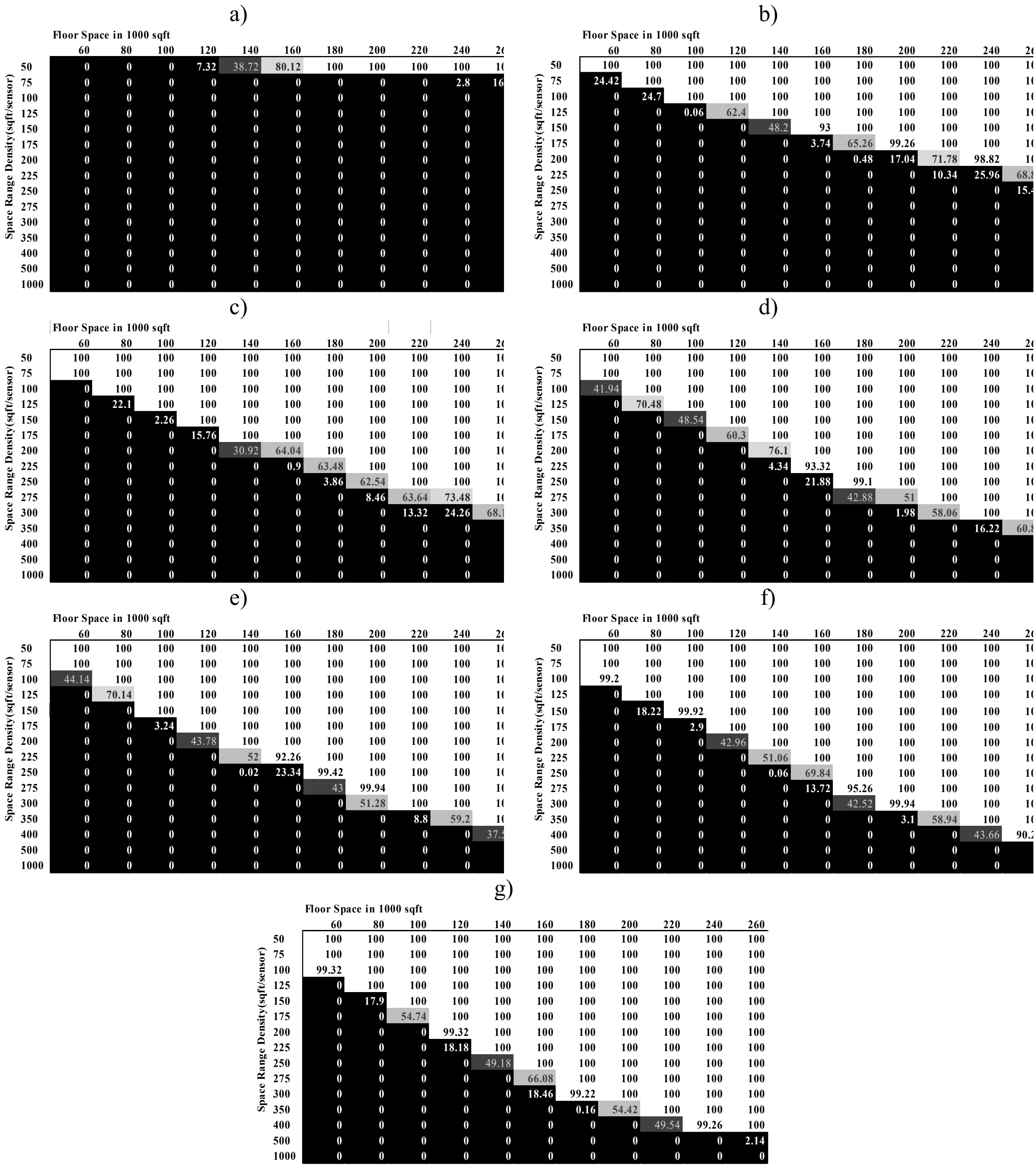


Figure 12: Generated Heatmaps for Different Time Periods of Data Collection Scenarios: a) 1 Minute, b) 5 Minutes, c) 10 Minutes, d) 15 Minutes, e) 20 Minutes, f) 30 Minutes, and g) 60 Minutes.

Furthermore, for a specific time period, the space range density corresponding to the breakeven point increased with the floor space. This observation is consistent with the conducted sensitivity analysis earlier, which highlighted that robotic systems become more favorable as floor space increased. These heatmaps provided valuable insights that align with the results of the sensitivity analysis, while also offering a probabilistic perspective that is closer to real-world scenarios. Facility managers can utilize these heatmaps to plan data collection strategies effectively, tailoring their approach to specific project requirements. By identifying breakeven points and understanding the probability of cost-effectiveness, decision-makers can optimize their choice between FWSN and MSR systems based on the unique characteristics of their building projects.

8.4 Limitations

While the developed LCCA framework provides a valuable decision-making tool for facility managers and stakeholders to identify the most suitable data collection strategy aligned with their building automation system (BAS) demands and operational goals it is not without limitations.

First, the framework is built on several simplifying assumptions to enable tractable comparisons. These include uniform floor space distribution, fixed labor requirements, and consistent sensor coverage across all buildings. In practice, building environments are rarely uniform, real-world structures often feature irregular layouts, multiple levels, and varied environmental conditions that can significantly influence installation feasibility and system performance. Moreover, price variability and operational differences represent an important limitation to the generalizability of the findings, as costs can vary substantially with operational complexity, payload, application type, and navigation requirements. However, the framework is designed to allow further sensitivity analysis or recalibration of parameters if applied to more complex or larger-scale case studies, enabling adaptable evaluation under varied operational contexts.

Second, although mobile sensor robots (MSRs) offer operational flexibility in dynamic environments, the study does not model the complexities associated with their real-world implementation. Challenges such as obstacle avoidance, dynamic path planning, and variable tour times caused by furniture layouts or partitions were not accounted for. Additionally, infrastructure requirements related to robot recharging cycles were simplified, and the need for real-time routing updates was not explored.

Third, the case study was conducted in the context of a developing country, specifically India where labor costs, electricity tariffs, and equipment procurement rates are generally lower, and environmental regulations such as e-waste disposal tend to be less stringent or inconsistently enforced. These economic and regulatory conditions are reflective of many Global South regions or developing economies that share similar cost structures and governance characteristics. For example, countries in the Middle East (e.g., UAE) often rely on a low-cost, predominantly South Asian migrant labor force; similarly, parts of Southeast Asia, Africa, and Latin America exhibit comparable infrastructure dynamics, regulatory flexibility, and pricing trends. In such settings, the relative cost-effectiveness of mobile sensing systems versus fixed networks is likely to remain consistent with our findings, making this framework transferable to a broader subset of developing or transition economies without substantial changes to key input parameters. However, the assumptions and results may not hold for high-income or highly regulated environments where compliance with stricter labor laws, privacy mandates, e-waste handling, and safety certifications can significantly alter operational costs and decision-making pathways. Thus, while the study offers broad insights for emerging economies, its application in developed regions should be preceded by localized contextual adaptation and sensitivity adjustment to align with local market conditions.

Finally, the study assumes a constant operational profile for buildings over a 50-year life span, consistent with standard lifecycle assessment practices. However, buildings often undergo functional and technological changes over time, including repurposing, renovation, or integration of newer sensing and automation systems. These changes may influence the relevance and performance of the initially selected data collection strategy. By recognizing these limitations, future research can work toward refining the framework and expanding its applicability to a broader range of building types and operational environments.

9. CONCLUSIONS AND FUTURE WORK

The study in this paper presented a comprehensive LCCA framework to compare two distinct data collection methods for IEQ monitoring, namely FWSN and MSR systems. A novel LCCA-based methodology that combined deterministic NPV calculations with probabilistic Monte Carlo simulations to address uncertainties in cost inputs was developed. The methodology was further validated through a case study encompassing small, medium, and large commercial buildings, which demonstrated the applicability and robustness of the methodology. Furthermore, sensitivity analysis and heatmap visualization were employed to offer deeper insights into the parameter dependencies and breakeven points between the two data collection systems.

The methodology systematically evaluated key cost components, including initial, O&M, replacement, and disposal costs, for both systems. Deterministic calculations identified conditions where each alternative was more economical, while Monte Carlo simulations quantified the reliability of these findings. The NPV computations demonstrated that for smaller buildings, FWSN systems were more economical due to their lower initial setup costs. Conversely, for larger floor spaces, MSR systems outperformed FWSN, offering scalability and flexibility that reduced per-unit costs as the monitored area increased. In particular, MSR systems were better suited for scenarios requiring long data collection intervals, where the operational efficiency of robots became a key advantage. These findings highlighted the importance of tailoring data collection strategies to the specific characteristics and requirements of the building environment. The conducted sensitivity analysis revealed that some key parameters such as the discount rate, floor space, sensor density, and time period of data collection, significantly influenced the economic feasibility of the two systems. Moreover, heatmap visualization further illustrated the impact of these variables and provided practical tools for decision-making.

While the proposed methodology proved effective in identifying the cost-effective alternative under different scenarios, it also pointed to limitations that warrant further exploration. For instance, assumptions regarding uniform floor space distribution, fixed labor requirements, and single-employee supervision may not be valid for more complex or dynamic environments, such as industrial facilities or multi-building campuses. Future research could extend the developed framework to account for these complexities, incorporating advanced modeling techniques or adaptive algorithms that better reflect real-world conditions. Other future directions could include integrating advanced machine learning algorithms for optimizing deployment strategies and refining scenario modeling. With such integration, future studies could also expand the framework to perform detailed case studies for developed countries, where higher labor costs, stricter regulatory environments, and diverse stakeholder needs introduce a broader range of variables. This would necessitate more sophisticated probabilistic modeling to accommodate the additional uncertainties and interdependencies inherent in such contexts. Additionally, incorporating real-time operational data could dynamically refine cost estimates, while extending the analysis to consider environmental and social sustainability metrics would further enhance the framework's comprehensiveness. Field validation of the LCCA framework in live operational environments would provide critical feedback to enhance its practical applicability and reliability across diverse global contexts.

In conclusion, the proposed LCCA framework serves as a valuable tool for facility managers and decision-makers to systematically evaluate and compare data collection strategies in indoor environments. By addressing economic feasibility alongside technical capabilities, this study paves the way for more informed and strategic investments in building automation and monitoring technologies. With further refinement and expansion, this LCCA-based framework can be universally applied to evaluate the cost-effectiveness of any two competing solutions for building data collection and monitoring needs.

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