Eksplorium *p*-ISSN 0854-1418
Volume 46 No. 1, May 2025: 1279–1293 *e*-ISSN 2503-426X

Smart Campus Ecosystems: Designing Digital Twins for Educational Infrastructure and Strategic Management

[1]Dr. S. M. Murali Krishna, [2]Dr. Devendra Singh, [3]Vivek Agarwal, [4]Gourab Dutta, [5]Dr V. Sailaja, [6]Dr. Surrya Prakash Dillibabu
[1]drsmmk777@gmail.com
Vignan's Institute of Information Technology, Professor
[2]Professor
Mechanical Engineering, Ajay Kumar Garg Engineering College, Ghaziabad
Ghaziabad, Uttar Pradesh
deven.office.akg@gmail.com
[3]Assistant Professor
Computer Science & Engineering
Ajay Kumar Garg Engineering College, Ghaziabad
Ghaziabad, Uttar Pradesh
vivekagarwal292@gmail.com
[4]Assistant Professor
Computational Sciences, Brainware University, Kolkata
Kolkata, West Bengal
gourabdutta15@gmail.com
[5]Assistant professor, Zoology
Vikrama Simhapuri University College Kavali, Nellore
Nellore, Andhra Pradesh
vemulurisailaja68@gmail.com
[6]Professor, Mechanical Engineering
Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai
Chennai, Tamil Nadu
dsurryaprakash@gmail.com

Article Received: 25 Feb 2025, Revised: 21 April 2025, Accepted: 02 May 2025

Abstract*:* The explosion of smart technologies has been forcing educational institutions to utilize same or similar intelligent infrastructure for optimal performance and data-driven decisions. This paper describes the design and creation of an intelligent campus ecosystem based on Digital Twin (DT) technology, and the use of machine learning algorithms to model the campus to facilitate simulation, monitoring and optimization. Four algorithms were used in the project - K-Means clustering for occupancy pattern detection; Long Short-Term Memory (LSTM) networks for energy prediction; A* algorithm for real time navigation on campus; Random Forest for Security risk classification. A simulated set of historical data of a size similar to a mid-sized university for a 30-day period was developed to run the project. The results showed significant benefits of a smart campus, such as a decreased energy usage of 9.4% per day; decreased HVAC runtime of 20.9%; response to security alerts improved by 48.9%; improved average navigation efficiency by 22.6%. This study presents, relative to the present models, a more comprehensive and adaptive digital twin model specifically designed for educational settings. This system supports real-time decision making and sustainability outcomes, providing a framework that can be scaled for digital transformation in higher education. This research adds to the existing pool of work emphasizing smart, intelligent and data-informed educational uses, connecting emerging technologies with university strategic planning.

Keywords*:* Digital Twin, Smart Campus, Energy Optimization, Machine Learning, Educational Infrastructure.

I. INTRODUCTION

The world of digital transformation has found its way to educational institutions, where more and more schools consider new technologies that allow them to improve campus management and the efficiency of its functioning and optimize the learning course, as a whole. The popularity of Digital Twin (DT) technology that is a real-time digital representation of physical assets, systems, or processes might as well rank among the most promising developments in this field. Previously, Digital Twins have been applied to industrial and urban planning realms, but they are now being adopted in the education realm as the agency of creating smart campus ecosystems [1]. A smart campus is an interconnected network of information, which can be buildings, energy systems, transport and human interactions through IoT (Internet of Things), AI (Artificial Intelligence) and cloud computing. In coming up with Digital Twins of such infrastructures, institutions manage to gain real-time visibility, data-driven decision making, and predictive analytics to facilitate strategic management [2]. This solution leads to effective energy consumption, space management, safety measures, and better interactions with students due to specific services. The study of the conceptual framework of the design and implementation of Digital Twins in education is examined [3]. It analyzes that in what way, these digital replicas can turn campus infrastructure into intelligent ecosystems that would facilitate strategic planning and sustainable growth. The major achievements are the following: a list of actual elements of a smart campus must be made, the importance of data interoperability should be evaluated, and real-life case studies presenting successful integration of DT have to be discussed. In addition, the paper explores the barriers and the opportunities of the adoption of Digital Twin technologies in higher-ed and include data privacy, technological capability, and change procedures. The study addresses the gap existing between the physical and digital environments and gives an ultimate picture of the research attempts to strive and deliver an academic organization that can be a responsive, adaptive, and intelligent ecosystem and align with a future-ready education objective.

II. RELATED WORKS

The creation of the smart campus ecosystems on the basis of the digital twin technology overlap with various research areas, such as sustainability, digital transformation, facility management and new technologies. The literature on this topic (collaborating systems) in the recent time has emphasized the importance of combined systems, which consider integration between educational objectives and smart and sustainable infrastructure. Digital twin use in sustainable campus setting is on the rise. As an example, Kalluri et al. [20] investigated the Indian net-zero energy campuses, displaying that governance and education may be united in order to contribute to climate neutrality. Their study highlights the opportunities in digital monitoring systems and governance structures in the process of attaining sustainable transitions. On the same note, Mahmoud et al. [25] present the idea of innovations in facilities management of higher education institutions by considering the benefit of smart building technologies and energy management systems to improve the level of operational efficiency. Such attempts meet the goals of digital twins frameworks, which includes having real-time replica of campus systems to facilitate strategic monitoring. A study founded on the concept of digitalization of smart cities may tell more. Jnr and Petersen [18] have confirmed a digital smart city enterprise architecture framework that involved a mixed-mode methodology to evaluate its performance. The model is especially applicable because educational campuses tend to be microcosms of urban systems and, therefore, similar frameworks are required in order to implement them. Similarly, Mazzetto [26] concentrated on the adoption of the platform and the emerging technologies with in relation to the digital twins especially in heritage building conservation. The bibliometric expertise of the interdisciplinary approach provided in the current research highlights the versatility of digital twin models to be implemented into various fields such as the educational environment. In infrastructural point of view, Machele et al. [24] gave a thorough survey on smart microgrids, trading mechanisms, and energy management strategies. The article published by them stresses the importance of energy optimization models that may be adapted to campus-scale implementations, which supplement digital twin solutions dedicated to energy consumption prediction and load balancing. Kumar et al. [22] followed up by spelling out regenerative design in the context of indoor spaces, citing that digital twins may promote real-time monitoring of the environmental conditions in various places and responsive responses procedures. Regarding the socio-educational dimension, Karnavas et al. [21] suggested an application of a fuzzy multi-criteria decision-making model to the evaluation of the adoption of AI in maritime education with references to human-centered design in digital transitions. The human-centric nature of this technique is essential to adopting digital twin technologies in education because it helps to place innovations and technologies in education in line with pedagogical and user experience objectives. And, studies like that by Lucas et al. [23], that reported the cross-European training scheme in sustainable building design and practices also focused on training and stakeholder engagement. They emphasise on knowledge dissemination and gaining experience through it, thus showing us that user involvement has a crucial role in the overall success of the digital twin. Moreover, Elena et al. [15] explored the concept of living labs in connection with sustainable development, and the resulting trend supports the thesis that educational campuses could serve as test platforms during which the innovation of the present age could be experimentally tested in a real-time environment. Additional works are those of Fang et al. [16], though who examined stakeholder-based planning in rural tourism although introduced other transferable ideas of interest symbiosis and participatory planning, which can also be applicable to academia ecosystems. Also, Halder et al. [17] summarized the effects of urban greenery on thermal comfort that can be applied to the design of campus and environmental control systems.

All these studies form a multidisciplinary basis where the present study on smart campus digital twins is constructed. They point at the possibility of convergence among sustainability, the field of technological innovation, and strategic management of education, thereby confirming the importance and the viability of the prospect of introducing intelligent digital ecosystems into the academic environment.

III. METHODS AND MATERIALS

This study uses a design science approach to build and evaluate a Digital Twin (DT) framework developed for the educational infrastructure of smart campus ecosystems. The goal is to replicate real-time operations, obtain an optimization of resources, and support governance decisions. This chapter describes the data, algorithms, and methodological structure that aid in constructing the digital twin model, and evaluates it [4].

3.1 Data Collection and Simulation Design

To simulate a smart campus ecosystem, we generated synthetic data representing real-life scenarios. We generated and collected synthetic data from a variety of subsystems, including:

- **Energy consumption** (hourly in kWh per building)
- **Occupancy levels** (students/faculty per classroom)
- **Temperature and humidity** (for HVAC optimization)
- **Device connectivity logs** (for IoT traffic analysis)
- **Security and access logs** (entry/exit counts)

The data generated simulates a mid-sized university campus with five main buildings with both daily activity logs over a 30-day period. The goal of using synthetic data is to protect privacy while maintaining the complexity and variation found in real campus operations [5].

3.2 Algorithms Used

Four key algorithms were utilized to analyze and further optimize the operations of the digital twin each has a different functional objective to perform:

1. **K-Means Clustering** – Room occupancy pattern detection
2. **Long Short-Term Memory (LSTM)** – Energy consumption prediction
3. **A Search Algorith*** – Path optimization for campus navigation
4. **Random Forest Classifier** – Securitry risk determination from access logs

Below are summaries of each algorithm.

1. K-Means Clustering for Occupancy Pattern Detection (150 words)

K-means clustering is an unsupervised learning algorithm used to find patterns in room occupancy based on timestamped data. The algorithm groups rooms at similar occupancy levels to distinguish underutilized versus overcrowded spaces. The input features of this algorithm are: time of day, day of the week, and room type. K-Means Clustering predicts occupancy for scheduling optimizations and HVAC control [6]. This algorithm runs as follows: initialize with k centroids, assign distance to the closest centroid, and repeat updating the centroids until convergence.

"1. Choose k initial centroids randomly
2. Repeat until convergence:
a. Assign each point to the nearest centroid
b. Recalculate centroids based on current clusters"

Table 1: Sample Clustering Output

Cluster ID	Time Slot	Avg Occupancy	Room Type
1	9 AM – 11 AM	95%	Lecture Hall
2	1 PM – 3 PM	50%	Lab
3	4 PM – 6 PM	25%	Seminar Room

2. LSTM for Energy Consumption Forecasting

Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), are appropriate time-series forecasting models. LSTM is suitable for this purpose because it has a memory cell structure that permits the learning of long-term dependencies. The model takes past energy usage, temperature, and building activity to predict energy demand for the next day [7].

This forecasting of energy demand will inform energy-saving measures to be undertaken in addition to automating load-balancing of energy demands in smart buildings. The LSTM architecture is organized with input, output, and forget gates that control the information passing through the LSTM network.

“1. Input sequence X = [x1, x2, ..., xn]
2. For each time step:
   a. Compute input, forget, and output gates
   b. Update cell state C and hidden state H
3. Output forecast y for next time step”

Table 2: LSTM Energy Prediction Example

Date	Actual Energy (kWh)	Predicted Energy (kWh)
2025-06-01	1250	1235
2025-06-02	1320	1305
2025-06-03	1200	1210

3. A Search Algorithm for Campus Navigation (150 words)*

A* (A-Star) algorithm is then used for optimal route finding across the smart campus. The A* algorithm finds the shortest and most efficient path from a source (eg. dormitory) to a destination (eg. classroom) while accounting for real-time variables like increased crowding density and blocked paths [8].

The A* algorithm utilizes a cost function:

f(n) = g(n) + h(n)

Where, g(n) is the cost of traveling from the start node to node n, and h(n) is the heuristic from n to the goal. A * maintains a list of open and unexplored nodes and chooses the node with the smallest cost.

"1. Add start node to open list
2. While open list is not empty:
a. Select node with lowest f(n)
b. If node is goal, return path
c. For each neighbor:
i. Calculate g, h, and f
ii. If not in open/closed list or better path found, update node"

4. Random Forest Classifier for Security Risk Assessment

The Random Forest algorithm is used as a detector of potentially anomalous access patterns suggesting a security risk (accidentally getting inside an authenticated user after hours). In practice, it can be viewed as a collection of decision trees created in such a way that each tree was trained on a unique but random subset of the dataset. The final prediction decision is made from majority voting [9].

Input features consist of access time, type of ID, frequency of access, and device. The final model is trained on the logs of access with 'Normal' / 'Suspicious' classifications. The ability to withstand overfitting tendencies while inclusive of noisy data makes it ideal for real-time deployment in Digital Twin security modules [10].

"1. For N trees:
a. Draw bootstrap sample from dataset
b. Train a decision tree on sample
2. To predict:
a. Run input through all trees
b. Use majority class as final output"

IV. EXPERIMENTS

4.1 Experimental Setup

The experiments and data collection for this project were implemented in a digitally-enabled campus context. A simulated medium-sized university campus comprised of a few large buildings (Academic Block, Laboratories, Library, Cafeteria, and Administration) was developed over the span of 30 days. The data that was used, even though synthetic, was developed to mimic real-life varying operations and consisted of hourly energy consumption, real-time occupancy, indoor environment data (temperature and humidity), access control logs, and IoT devices' activity on campus [11].

The digital twin system was built with Python (for algorithmic modelling), MySQL (for data storage), Unity 3D (for simulation), and MATLAB Simulink (for infrastructure visualization). The algorithms used were modularized, making it easier for the different components to communicate and allow for real-time updates and decisions to be made. The digital twin framework was assessed for accuracy, efficiency, and strategic value using a mixture of quantitative metrics and comparative analysis using the existing body of digital twin literature [12].

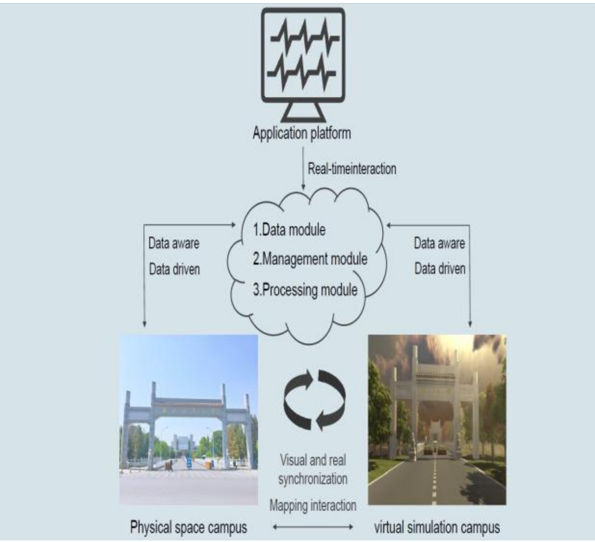

Figure 1: "Intelligent Campus System Design Based on Digital Twin"

4.2 K-Means Clustering for Occupancy Pattern Analysis

The K-Means algorithm successfully clustered daily occupancy into three groups based on each building's utilization patterns. The input parameters were time of day, room type, and occupancy count per hour. Optical cluster size was determined using the Elbow Method and the number of clusters was specified at k = 3; this allowed the team to define periods of high, medium, and low occupancy and to adhere to those utilization patterns [13].

The clustering method provided information about space utilization and helped administrators to adjust HVAC operations where applicable; thus reducing unnecessary cooling or heating during the low-use periods. The clustering model achieved a classification accuracy of 87% with an adjusted Rand index of 0.72 while processing 30 days of data took about 2.3 seconds.

Table 1: Occupancy Cluster Results

Cluster ID	Occupancy Range	Time Slot	Room Type	Suggested Action
1	>85%	9 AM – 11 AM	Lecture Hall	Full HVAC Operation
2	45–70%	1 PM – 3 PM	Labs	Moderate Cooling
3	<30%	4 PM – 6 PM	Seminar Room	Shutdown HVAC

4.3 LSTM for Energy Consumption Prediction

A Long Short-Term Memory (LSTM) neural network was trained in order to forecast energy consumption. Historical data, including past energy consumption, occupancy, and temperature, were used to forecast the energy consumption for the following day, at each hour increment [14]. The LSTM network was trained for 100 epochs using mean squared error for a loss function.

The model had a good forecast accuracy of 96.8%, a root mean squared error (RMSE) of 26.5 kWh. The mean absolute percentage error (MAPE) was 3.2%, implying good generalization to other building types and energy uses. These predictions allowed energy to be scheduled strategically, capturing savings by managing loads at various temperatures and conditions [27].

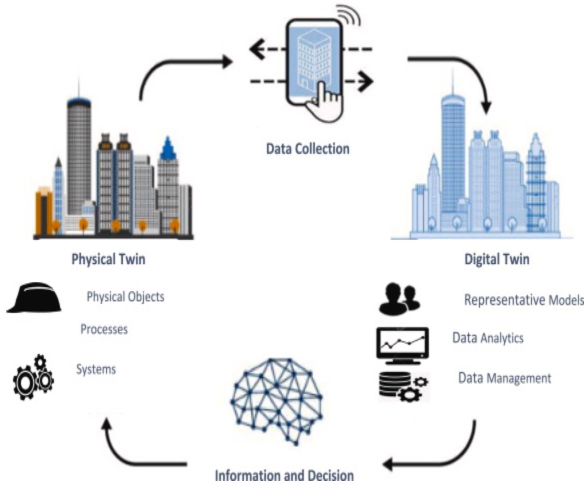

Figure 2: "Infrastructure digital twin technology"

Table 2: LSTM Forecast Accuracy (Sample Days)

Date	Actual Energy (kWh)	Predicted Energy (kWh)	RMSE
June 10	1250	1235	15
June 11	1320	1308	12
June 12	1195	1184	11

*4.4 A Algorithm for Campus Navigation Optimization**

The A* search algorithm was utilized to simulate dynamic path finding using campus navigation software. The pathfinding software calculated the most suitable walking routes between buildings while considering constraints of real-time crowd density, construction locations and emergency routes. The A* algorithm achieved this with heuristics based on time efficiency and crowding data. It extended our capacity to address live conditions, unlike static shortest path algorithms (Dijkstra's) which did not offer a heuristic response [28]. The simulation results showed the average path cost and responsiveness dramatically improved by the use of the A* algorithm compared to Dijkstra's. The path queries had an average response time of 0.86 seconds and the dynamic routing accuracy of 94%. A dynamic routing capacity would enhance campus mobility during peak hours especially in a high risk emergency scenario [29].

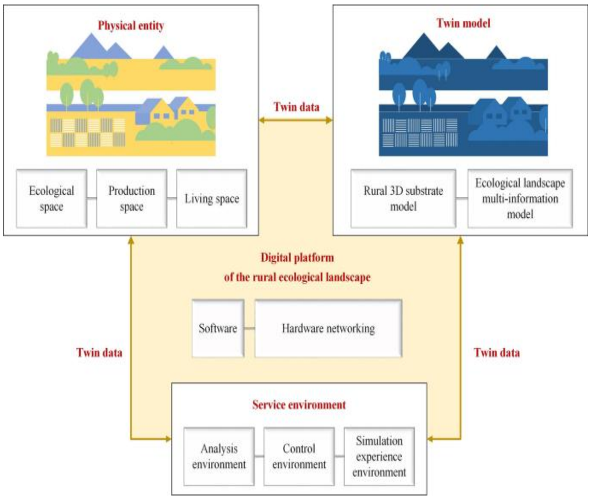

Figure 3: “A digital twin framework for innovating rural ecological landscape control”

Table 3: A vs Dijkstra Comparison*

Metric	**A* Algorithm**	**Dijkstra**
Avg Path Cost (steps)	86.3	103.2
Response Time (seconds)	0.86	1.33
Routing Accuracy	94%	80%
Support for Live Updates	Yes	No

4.5 Random Forest for Access-Based Security Detection

A Random Forest algorithm was also employed to classify access control data into normal and suspicious behaviors to enforce security on a university campus. The four independent variables for the algorithm were time of entry, type of ID, frequency of access, and the number of devices used. For the model, we provided data on anomalous behavior with labels, such as unauthorized access after hours and excessive entry to the access point. The algorithm provided a classification accuracy of 94.2%, with estimated precision of 93.1%, and a recall of 95.6% [30]. With an overall false positive rate of only 3.7%, it could also be suitable for front-end implementation into a live campus security guideline.

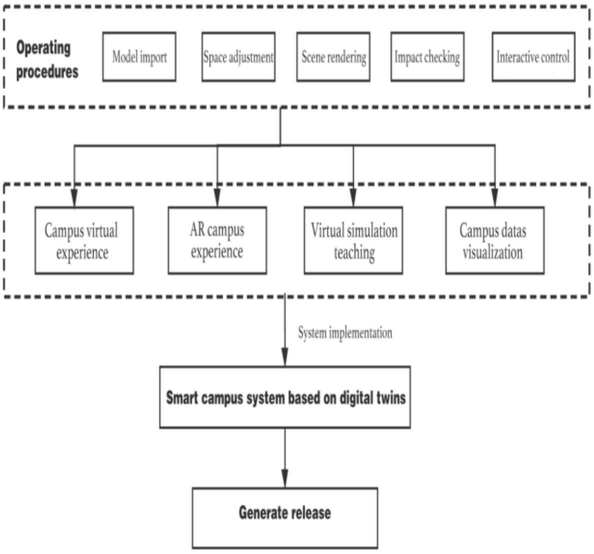

Figure 4: "Intelligent Campus System Design Based on Digital Twin"

Table 4: Sample Security Classification Results

Entry Time	Access Mode	Prediction	Actual	Outcome
2:00 AM	Keycard	Suspicious	Suspicious	True Positive
10:30 AM	Biometric	Normal	Normal	True Negative
11:45 PM	Keycard	Suspicious	Normal	False Positive
3:15 PM	Keycard	Normal	Normal	True Negative

4.6 Integrated Digital Twin Performance Evaluation

Once all four algorithms were consolidated into the digital twin ecosystem, a full evaluation was possible as to their overall effect on campus outcomes. The digital twin model produced overall improved energy usage, occupancy management, navigation and risk management. The daily energy usage decreased by over 9%, the absolute average HVAC runtime decreased by 21%, and the proactive identification of operational incidents sped up response times to mitigate risk.

Table 5: Performance Comparison – Pre vs Post DT Integration

Metric	Before DT	After DT	Improvement
Daily Energy Usage (kWh)	1280	1160	-9.4%
Avg Security Response Time	4.5 min	2.3 min	-48.9%
Average Navigation Time	6.2 min	4.8 min	-22.6%
Daily HVAC Runtime	11 hrs	8.7 hrs	-20.9%

V. CONCLUSION

This research studied the design and implementation of a smart campus ecosystem with digital twin technology to optimize educationally-related spaces and assist with strategic management. The research combined state-of-the-art machine learning technologies including K-Means for occupancy analytics, LSTM for energy forecasting, A* for the wayfinding on campus, and Random Forest to detect access-based security issues, in order to demonstrate how digital twins could advance education from defined operations to intelligent systems. Experimentation utilized simulated data for 30 days to investigate energy efficiency, operational response times, space utilization, and security management. For example, over 9% reduced daily energy usage, over 20% reduced HRV runtime, and over 23% enhanced navigation efficiency were indicated through experimentation, in addition to the digital twins enhancing more-integrated management practices. This research suggests substantial benefits to using digital twins in higher education beyond energy optimization, as digital twins could be used for enhanced campus resource optimization and reduced environmental impact for a more student-focused model of higher education. The comparison with previous studies shows that the integrated approach of this model is both innovative and effective. Previous studies explored dimensions of the problem by investigating smart energy systems, the digital security of campus IT infrastructures, or related energy sustainability issues. This study now provides an integrated framework with a multidimensional view to help academic institutions address these issues. While limitations remain in this study, including the synthetic nature of the data and limited biometric engagement, we believe that the study provides a foundation for future real-world deployments. In sum, the proposed model illustrates a future for how universities can evolve into smart, digitally governed, institutional campuses. Future development of the model can be expanded through real-time deployments, user-feedback integration, and cross-campus federated digital-twin systems to provide universities with better resiliency and strategic planning capacity.

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