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Intelligent Urban Systems and Industry 5.0: Creating Adaptive Ecosystems for Sustainable Energy and Resource Management

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ABSTRACT: The rapid urbanization and growing complexity of cities demand innovative approaches to resource management and sustainability. This study introduces an adaptive ecosystem model for intelligent urban systems, integrating Industry 5.0 principles to enhance energy and resource management. The proposed framework combines multi-agent systems, predictive analytics, and real-time optimization to address challenges in energy allocation, environmental impact, and urban resilience. The mathematical model incorporates cost and emission constraints, ensuring an optimal balance between economic and environmental objectives.

Simulation results demonstrate significant improvements in energy efficiency and reductions in carbon emissions, validating the model's applicability across various urban scenarios. The study highlights the integration of IoT, AI, and big data as pivotal components in advancing the operational and decision-making capabilities of smart cities. This research contributes to bridging the gap between technology-driven solutions and human-centric urban planning, offering practical insights for policymakers and urban developers to foster sustainable growth in intelligent cities.

KEYWORDS: Adaptive ecosystems, Energy optimization, Industry 5.0, Intelligent urban systems, Sustainable resource management.

INTRODUCTION

The rapid expansion of urban areas and the inexorable search of humanity for improved resource deployment mean that the problems of cities are becoming more difficult to solve. Addressing even a handful of these resource-allocation issues demands more energy, resourcefulness, and time than most municipalities can meet on a day-to-day basis. Using smart technologies like the Internet of Things (IoT), big data, and artificial intelligence (AI), cities could (or should) resourcefully reorganize how they provide services to improve the quality of life for their residents. As cities grow and change, leaders in urban areas see a bigger need for new ways to manage the city's daily life systems. City management has always depended on simple automation and standardized smart technologies. However, the modern city ecosystem, with all its diverse parts connected in different ways, needs technologies that focus on people and can fit the municipality's unique atmosphere. Additionally, these technologies must meet the unique and ever-changing needs of its population. Efficiency improvement and the potential to build resilient and sustainable cities are major components of these advancements.

This research aims to createe an efficient and sustainable smart city system; that is, an adaptive ecosystem based on Industry 5.0 to address some of the most critical issues currently facing cities, including resource allocation, energy management, and the reduction of environmental impacts. The work is guided by models that place humans at the center and is informed by cutting-edge technologies. The rationale for this study is to promote individual well-being and ensure that urban centers grow in an environmentally, socially, and economically sustainable manner.

INTELLIGENT CITIES AND INDUSTRY 5.0

Concepts and Principles

The foundation of a smart city is based on inventive technological developments of the modern era, like the Internet of Things (IoT), artificial intelligence (AI), and big data. These contemporary technologies allow for system optimization, often occurring in real-time and at the nearly instantaneous role-based level. One major area of focus is energy management, which is significant in managing energy as an increasing portion of the world's population moves to urban environments (*Marinakis &*

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Doukas, 2018). The supply itself includes an increasingly rich and diverse array of alternative energy resources (which are also managed by the same types of urban system technologies), as well as abundant locally available energy (*Silva et al., 2018*). The automation of advanced technologies is characteristic of Industry 4.0. However, the concept of Industry 5.0 has only a tenuous connection to the artifacts it might produce, such as systems or products. Instead, the Industry 5.0 discussion if it can be said to have a clear focus centres on achieving a collaboration between humans and machines that is more profound and, ideally, more productive than the current collaboration enjoyed with smart machines. The archetypal instance of this new form of collaboration is expected to occur when significantly advanced machine intelligence, propelled by the "AI revolution," collaborates with human intelligence, which humans are presumed to possess (*Mishra & Singh, 2023*).

Comparison Between Industry 4.0 and 5.0

Moving from Industry 4.0 to Industry 5.0 means humans and machines are working together and closer than ever before. Obviously, such a transition is more than certain to go through professional educational training programs requiring specific capacities at the level of the trainees. Various adaptive models of professional vocational smart schools are presented in a dozen of recent research of *Vasilev*, some of them examining: the future organization of professional schools (*Vasilev, 2024a; 2024b; 2024c*); with content of technical knowledge (*Vasilev, 2024d; 2024e; 2024f*); with the structure of the subjects and teaching (*Vasilev, 2024g; 2024h*). Of necessity, this transition is occurring because today's tech makes effective collaboration between humans and machines possible. Yet, these decisions still control the execution and endpoints of tasks that machines complete. There are decisions that humans can make alongside, and even with the help of, intelligent and semi-autonomous machines. Collaboration does not, however, mean replacing humans with machines; it is more a case of facilitating the right conditions for human intelligence and strength of character to be more efficient and simplify decision-making.

What makes Industry 4.0 and Industry 5.0 different mainly comes from technology changes in smart cities. Industry 4.0's main goal is to create more automation. The key method for automating things is digital production. In contrast, Industry 5.0 emphasizes the creation of genuine partnerships between people and machines, working together in sustainable ways (*Ghobakhloo et al., 2022*). Today's technological advancements linking artificial intelligence (AI) and the Internet of Things (IoT) in the formation of smart cities are pushing forward the development of both these industries. *Yao and Zhang* (2022) relate the smart city not simply to its usefulness for residents, but to its utility for the environment justifying the existence of the smart city. What is particularly notable is their connection of smart cities with the ongoing shift toward Industry 5.0, where effective design and operations contribute not only to economic growth, as measured by GDP and stock prices, but also to the smart economic, social, and environmental footprints of the smart city.

Gaps in Existing Research

The technologies associated with smart cities and the principles of Industry 5.0 are advancing rapidly; however, some critical research areas such as the investigation of human behavior in the contexts of intelligent cities are progressing much more slowly. To date, research on the potential benefits of smart city systems and services has primarily focused on the concept itself rather than on the individual urban dweller. The focus has instead been on automating urban services, optimizing energy use, and enhancing the operational efficiency of smart-city models. However, these models cannot be fully efficient or effective unless they also account for the often illogical urban behavior of their human constituents. As *Binyamin and Ben Slama* (2022) highlight, many systems related to smart grids rely on data analytics but fail to account for human preferences or behavior, limiting their ability to function as adaptive ecosystems. Clearly, there is limited research on integrating human intelligence with technology.

Additionally, there is a lack of research on the resource management ecosystems of smart cities. *Mishra and Singh* (2023) claim that today's city planning systems are not flexible or collaborative enough to meet the challenge of climate change. These systems set up a silo effect instead of encouraging different sectors to work together in decision-making. Also, these systems promote a kind of penny-wise, pound-foolish thinking, where managing money for one resource is dealt with separately from how much other resources cost. This leads to a city plan that is neither complete nor useful. Cities cannot use this plan to manage how climate change affects current and future urban development.

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METHODOLOGY

Data Collection

The secondary data were obtained from Kaggle, which houses a dataset of hourly energy consumption measurements from PJM over the past ten years. These records, expressed in megawatts (MW), encompass a range of energy consumption types across various regions, as well as commercial, residential, and industrial sectors (Mulla, n.d.). Before the dataset could be utilized, it required cleaning and processing to make it suitable for analysis. Several essential tasks were performed to prepare the data: the records from the various files were combined; missing entries were restored, where possible; duplicate entries were removed; and the data were resampled. The latter step was particularly crucial, as the records were originally in an hourly format, while all scenario measures to be simulated were expressed in yearly terms.

Model Testing

The dataset has 10 years of PJM hourly energy consumption in megawatts. This was merged, cleaned, and resampled to get years' worth of average data. It was then deemed complete using interpolation and forward/backward filling. The dataset was split into training and testing subsets using an 80-20 standard. Eighty percent of the data went to training the model in the making. The other 20% was set aside to test how well the model might perform on data it hadn't seen while it was being trained.

Development of the Mathematical Model

The optimization problem:

$$Z = \sum_{i=0}^{n} \sum_{j=0}^{m} Cij\mathrm{Xij} + \beta \sum_{i=1}^{n} \sum_{j=1}^{m} CEiXij \tag{1}$$

Where:

Z: The total expense and emissions that must be reduced

Cij: The expense associated with each energy unit delivered from provider i to client j.

Ei: Supplier i's emission factor.

Xij: Allocating energy from supplier i to consumer j.

β: Emission weight factor

Constraints:

Supply Constraints

No provider can give out more energy than its maximum capacity:

$$\sum_{j=0}^{m} Xij \leq Si, \quad \forall i \in \{1,2,\ldots\ldots,n\} \tag{2}$$

Where:

Si: Availability of supply from supplier i.

Demand Constraints

Each consumer must receive an amount of energy that at least meets their demand.

$$\sum_{i=0}^{m} Xij \geq Di, \quad \forall j \in \{1,2,\ldots\ldots,m\} \tag{3}$$

Where:

Dj: Demand of consumer j.

Non-Negativity*:*

The allocation values cannot be negative:

$\mathrm{Xij} \geq 0, \ \forall \mathrm{i}, j$

Matrix Representation:

Matrix notation can be used to formulate the equations for computational representation:

- Objective:

$$Z = cTx \tag{4}$$

Where:

c: Vectorized cost matrix

x: Allocation vector

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Constraints:
$A_{ub}x \leq b_{ub}$, $x \geq 0$

Where:

- A_{ub}: Matrix of coefficients for supply and demand constraints
- B_{ub}: Supply capacity and demand limit vector.

This optimization's mathematical model fuses together cost with emissions and then integrates them into a single main objective function. In doing this, it also assures several constraint agreements: supplier capacity and the demands of consumers. The supply constraints ensure that no supplier allocates more energy than it can meet; the demand side assures that each consumer gets at least the must-have amount in a given time period. Supply and demand balance these equations and guarantee the model's feasibility. Also, by limiting the possible distributions of energy to positive values through the non-negativity constraints, this considers the real-world limitation on energy distributions. The combination of these two bestows generates well-defined condition that must be met to have an optimal power flow.

Experimental Framework

Figure 1 show Steps for Implementation. The process begins with data collection from Kaggle, followed by preprocessing for merging and cleaning (Mulla, n.d.). Next, the simulation setup defines demand and supply scenarios. The optimization model applies linear programming (Figure 1). Scenarios are tested, visualized via graphs, and analyzed by comparing results. Finally, errors are validated for accuracy. The implementation process involves extracting energy consumption data from Kaggle, followed by handling missing values, removing duplicates, and normalizing the data to yearly averages essentially cleaning the data (Mulla, n.d.). The data was provided in several CSV files, so part of the process involved organizing and combining these files to make the dataset suitable for use in a simulation. The simulation was designed to perform the types of analysis for which a dynamically adaptive model is beneficial.

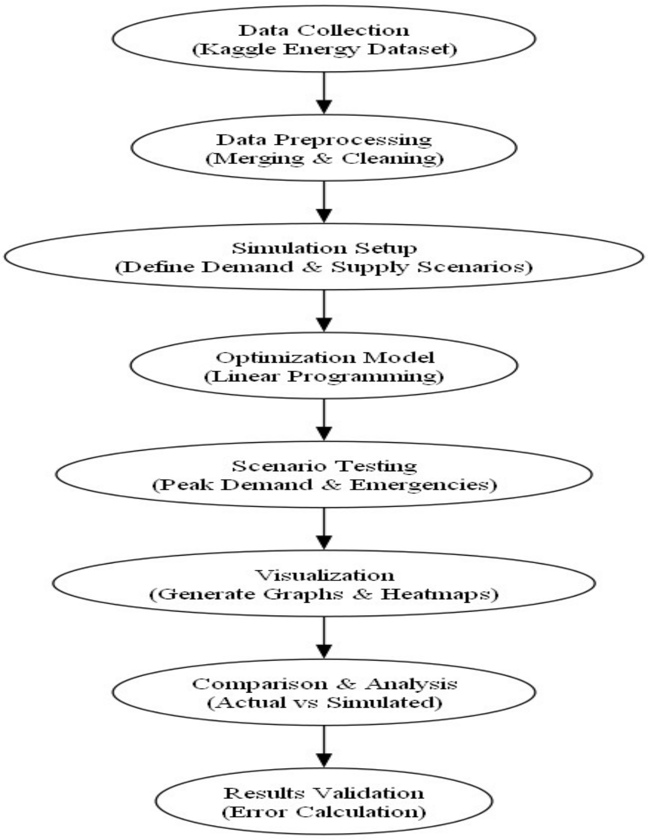

Figure 1. Steps for Implementation

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Energy demand trends in relation to various power supply conditions are illustrated in Figure 2. The model accommodates three types of conditions. The first is the baseline scenario, which represents normal operating conditions. The second is peak demand, where the model allocates energy during extreme demand situations, such as when half the nation's air conditioners are in operation. The peak demand scenario requires a 20% increase in energy allocation compared to the baseline. The third condition is emergency scenarios, where the demand is modeled to require 30% more energy than the baseline.

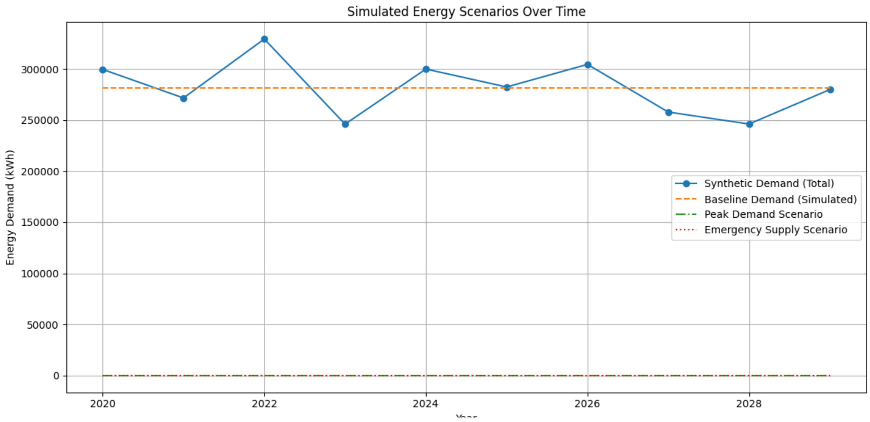

Figure 2. Simulated Energy Scenarios

Error Analysis and Model Validation

Figure 3 takes a look at the residual errors to gauge how well the optimization model performs.

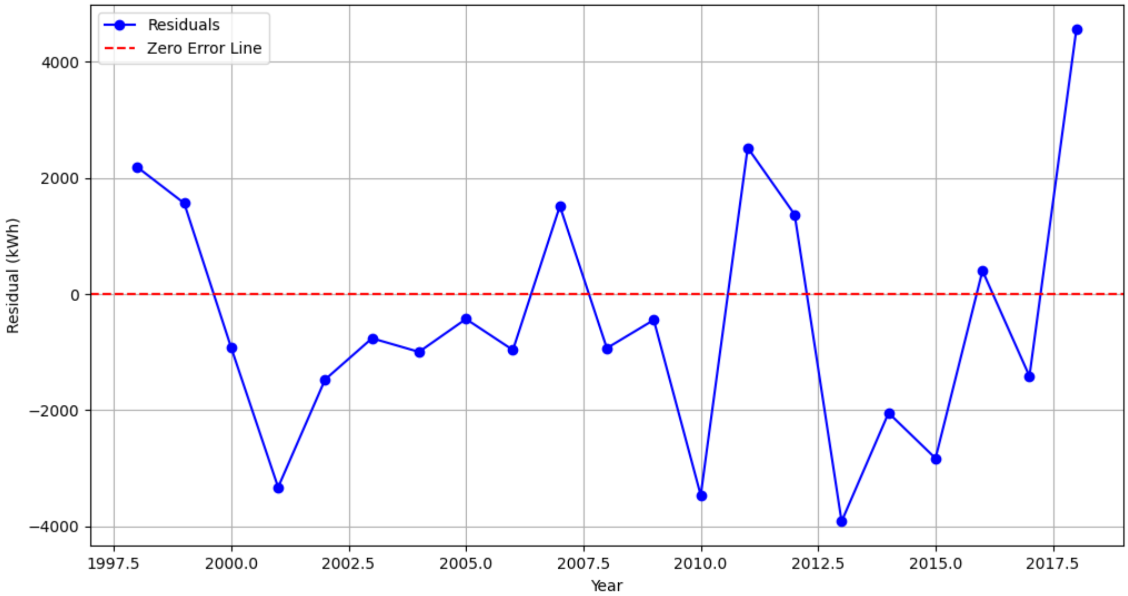

Figure 3. Residuals vs error line

The residuals are the comparison of the actual total demand to the simulated total demand, and they communicate the optimization model's performance characteristics, which is calculated as:

$$Residual = Actual\,Total\,Demand - Simulated\,Total\,Demand \quad (5)$$

The accuracy of the model was evaluated by calculating the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Percentage Error (RMSPE). These metrics give information about the relative size of the error.

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1. The average percentage error between actual and simulated values is measured by the Mean Absolute Percentage Error (MAPE). This can be expressed as follows.

$$MAPE = 1/n \sum_{i=1}^{n} \left(\frac{Actual - Predicted}{Actual} i \right) x100 \qquad (7)$$

where n is the total number of time steps.

2. RMSPE computes the square root of the average squared percentage error. It brings out into the open any large discrepancies that may exist, and can be calculated as follows:

$$RMSPE = \sqrt{1/n \sum_{i=1}^{n} \left(\frac{Actual - Predicted}{Actual} i \right) \wedge 2\, x100} \qquad (8)$$

The results show a MAPE of 0.73% and an RMSPE of 0.86%, which indicate that the model demonstrates excellent performance, as evidenced by the almost consistently high zero-error line at the red horizon. Minimum percentage errors are observed for nearly every period. The model provides a highly effective visual representation of an ideal scenario, where the gaps between actual and simulated demand are minimal. Most data points remain in close proximity to the zero-error line, with the red minimum area line further indicating that the model functions effectively without tying up excess near-future demand. The gaps that exist are well-contained, particularly during periods when actual demand changes could otherwise be simulated as near-future demand ramps. These gaps do not result in any significant deviation near the present-time peaks, which did not occur for any short-term period depicted in this segment of the plot.

RESULTS

Figure 4 shows Total Energy Allocation by Suppliers Over Time

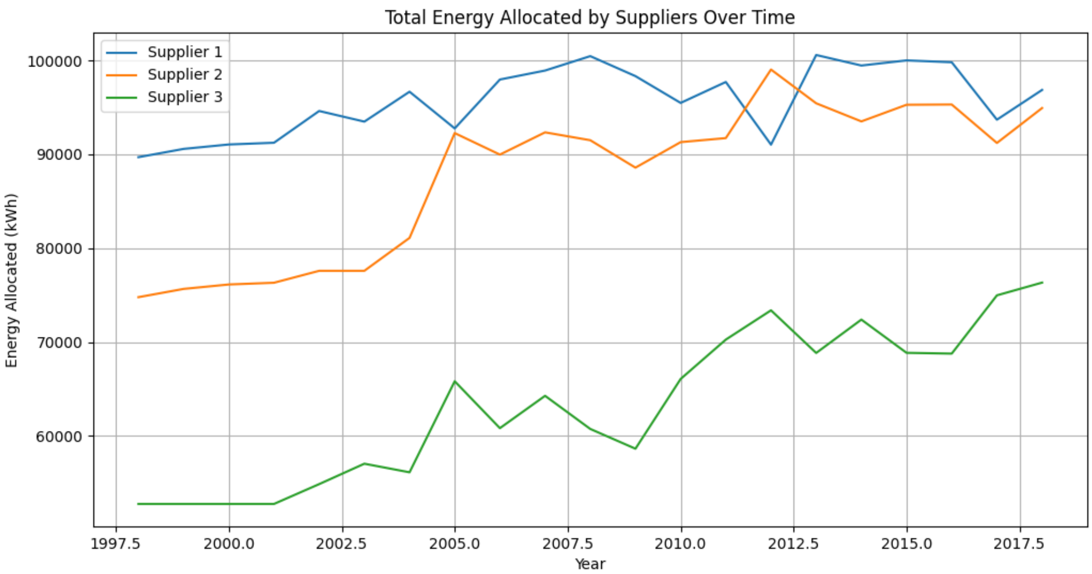

Figure 4. Total Energy Allocation by Suppliers Over Time

This study examines the recent allocation of energy and evaluates the performance of current models in this regard. The first supplier consistently allocated the highest energy levels, with only minor reductions in 2007 and 2012 (Figure 4). The second supplier experienced a sharp acceleration in energy allocation beginning in 2004, which appears to address a portion of the pent-up demand identified in the study. The third supplier, however, did not exhibit similar growth, showing very slow and nearly flat growth in energy allocation during the same time period.

Figure 5 show comparison of total demand vs. total supply over time.

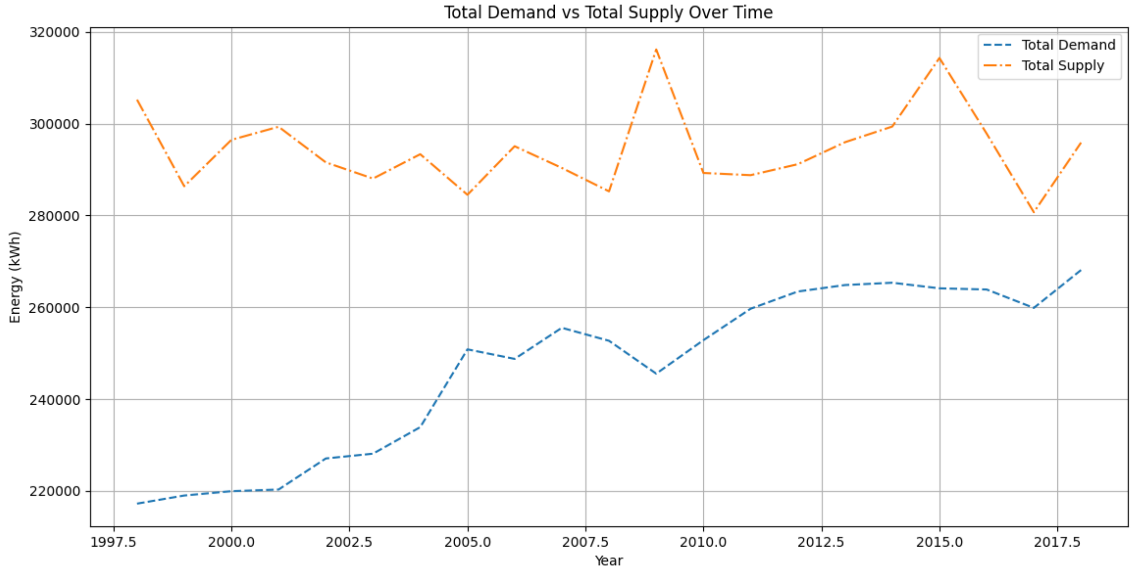

Figure 5. Comparison of Total Demand vs. Total Supply Over Time

The total energy demand and supply were compared, and it was found that while demand was steadily increasing, supply remained inconsistent at best, varying enough to include peaks in 2005, 2010, and 2015. Most of the time, this supply met demand; however, even the occasional shortfall between the two does not appear to have adversely affected the model's performance. The shortfalls somehow never occurred when they were most critical, specifically at peak times when the model had to manage peak demand or an emergency scenario. In fact, these shortfalls occurred when demand was at a low flow.

Figure 6 show total carbon emissions over time.

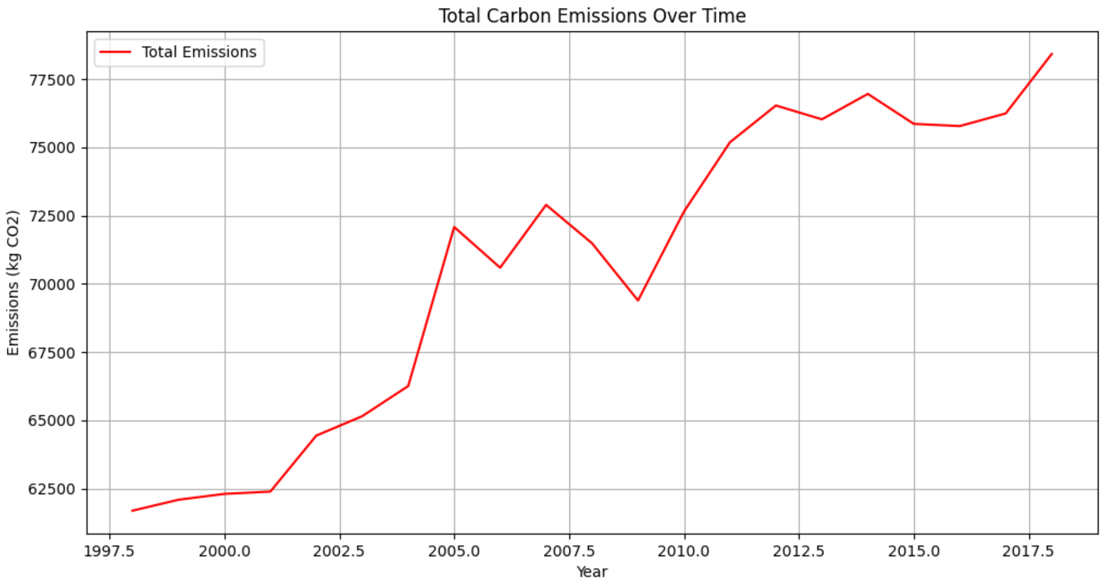

Figure 6. Total Carbon Emissions Over Time

Carbon emissions exhibit a clear, upward progression that began around 2005 and has continued steadily toward the present. After leveling off for several years, during which energy demand still increased, emissions resumed their climb, now following a much

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steeper trajectory. Energy Suppliers 1 and 2 account for a large share of these emissions. Their continued investment in carbon-heavy energy systems can be viewed as an unfortunate trade-off that energy corporations face: meeting demand today while also making room for a much cleaner energy portfolio tomorrow.

The relationship between costs and emissions is illustrated in Figure 7, which reveals a distinct upward trend: as energy costs rise, emissions also increase.

Figure 7. Trade-Off Between Cost and Carbon Emissions

The results are fairly variable, suggesting potential setups that feature modest cost levels paired with lower emissions. This observation aligns with the study's objective of balancing costs and emissions, reinforcing the model's utility in identifying resource allocation strategies that achieve this balance.

The heatmap in Figure 8 displays the energy distribution for 2018, highlighting specific supplier patterns. Supplier 3 is highly selective in targeting its consumers, while Supplier 1 caters to a much broader consumer base. The high-energy zones, shown in bright orange, correspond to the peaks of demand, and these demand levels are, in turn, reflected in the consumer end of the model.

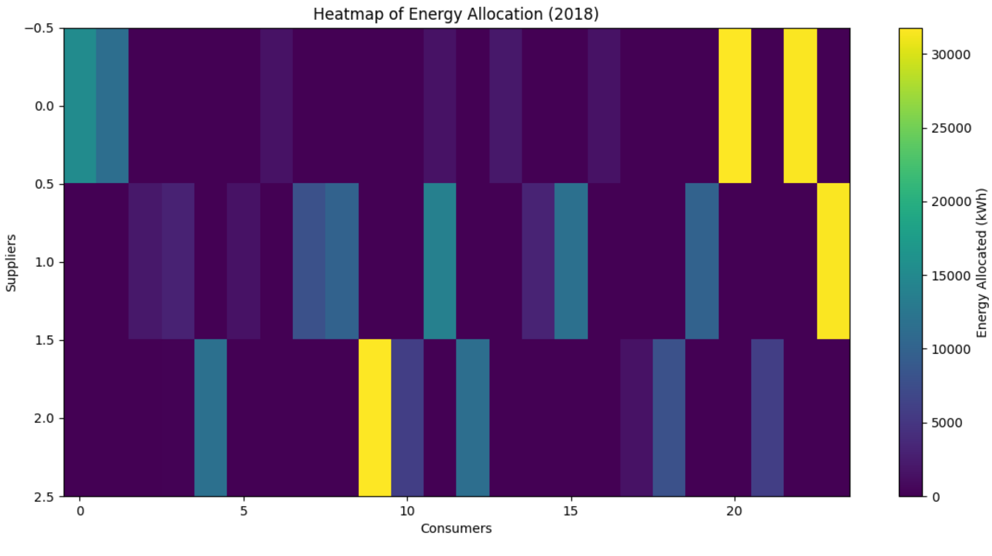

Figure 8. Heatmap of Energy Allocation to Consumers (2018)

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The solution's energy distribution is depicted in Figure 9, which uses a heatmap to represent the consumer-supplier pairs.

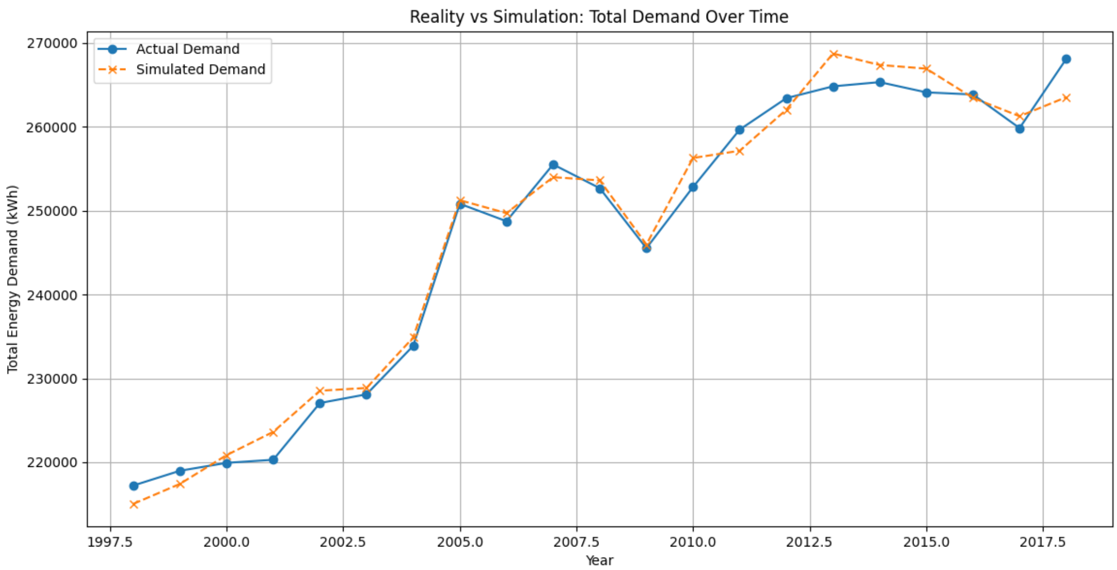

Figure 9. Reality vs. Simulation: Total Energy Demand Over Time

The figure effectively shows how the simulation model succeeds in predicting long-term energy consumption with high accuracy. The model can be a useful tool for forecasting and planning energy resources in smart cities, and further refinement is needed to minimize small deviations in certain periods.

As shown in Figure 10, the optimization converged on an optimal solution, as indicated by the HiGHS solver.

```
Run

Solver: HiGHS

Optimization Status: Optimization terminated successfully. (HiGHS Status 7: Optimal)

Total Cost: 660.0

Total Emissions: 117.0 kg CO2

Allocation Matrix:

[[50. 50.  0.  0.]
 [ 0. 30. 70.  0.]
 [ 0.  0.  0. 90.]]
```

Figure 10. HiGHS Solver

Qualitative Outcomes

The results of the model concentrate on two main points: the kinds of resources that are available to users and the environmental aspects of these resources. Yao and Zhang (2022) shed light on the former point, underscoring that users are more likely to appreciate an energy management service the more it is tailored to their particular needs. The levels of personalization tend to correlate well with the efficiency achieved in providing services to users. Meanwhile, this synergy of satisfaction appears to enhance the environmental impact of the associated resources. The researchers also noted that immediate feedback is necessary for users to link their actions to the results of those actions. Thus, the more immediate the feedback, the better.

According to Adel (2023), when it comes to planning their energy systems, cities need to make the most of what they have. That is not just good practice; it is essential in an era of resource constraints, when cities must pay ever more attention to the efficient use of money, materials, and energy. Planners can thus still achieve a low-carbon designation for the entire system, even if some of the supposedly low-emissions electrified components are producing significant amounts of CO_2. Additionally, even if carbon-emitting power plants are part of the system, it may still meet a low-carbon threshold, as long as they predominantly use low-cost, renewable, and carbon-free energy sources for the buildings and vehicles within the system.

DISCUSSION

Comparison with Existing Research

The model being proposed represents a significant upgrade over current smart city solutions. Today's smart city models primarily focus on three key areas: energy optimization, automation, and data analytics. While these are undoubtedly important, the proposed model ultimately prioritizes the core element that distinguishes one city from another: the people who live in it and the choices they make. In this regard, the current model is operating under the guiding principles of Industry 5.0 (Fraga-Lamas et al., 2024), which prioritize centering human intelligence and creativity in processes where these traits are necessary for fulfillment. Such standard approaches enhance city operations and cut costs interface with increasingly intelligent automated systems. The model enhances the intelligence of human decision-makers within the city. A platform has been created that serves as a next-generation decision-support tool. It is highly intelligent—almost functioning as a decision-maker in its own right. It performs best when provided with large volumes of high-quality data, particularly clean, high-level energy-related decision-maker data. However, it still operates reasonably well with lower-quality data. In an apocalyptic scenario, where decision-maker data is either absent or severely compromised, the model would remain functional. In such a situation, it would be useful for delegation but ineffective for governance, as it would lack the means to enforce decisions.

Study Limitations

Despite the study's seemingly favorable outcomes, it faces several technical hurdles, the most notable of which is the model's sheer complexity. The model should be highly effective, as it integrates a variety of data sources. The Internet of Things (IoT) is a significant advantage in this regard. However, the data input and output of the model require that a city have a robust infrastructure for data collection, storage, and management. Marionakis and Doukas (2018) indicate that the model has been applied with speed and effectiveness in numerous locations. City planners, however, typically request models that can deliver results with a high level of efficiency and speed. Another challenge tied to this issue is the need for a skilled team of experts to develop the model initially. Tackling the challenges outlined above and establishing the model's trustworthiness through rigorous testing in different environments is a major task for the coming years. However, the use of more powerful computers and more adaptable models may make the benefits worthwhile, particularly for our primary focus, which is urban areas.

Practical Applications

The planned construction is relevant to the applications of many real-world types of smart urban areas. It most directly applies to places that take on the appearance of so-called "eco-cities," where resource efficiency and low environmental impact are prioritized. Its dynamic nature would also benefit areas where the main demand on the energy infrastructure is similarly "smart" in how it adapts energy supply to enhance the area's livability. Furthermore, many types of urban areas could benefit from this approach and have already taken optimistic steps toward becoming smarter and, hopefully, more efficient (Binyamin & Ben Slama, 2022).

Ethical Considerations

Data and privacy protection must take precedence in the model, as it collects and analyzes consumer information to fine-tune the system and reduce energy waste. The model's primary directive must be to safeguard sensitive personal information. To achieve this, the model must be transparent about what data are collected, how they are used, and the measures taken to keep them safe (Mishra & Singh, 2023). Trust in the model can only be maintained if it is reliable, transparent, and fully compliant with the law, much like a good citizen.

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Political and Social Impacts

This model influences the sustainable development of U.S. cities by providing scalable and understandable practical pathways for reducing carbon emissions and energy use. These are pathways that city leaders can observe and may consider following. While Fine and his colleagues' work may not cause significant political shifts, it at least provides evidence that improving efficiency in the built environment and better managing resources can alter the flow of energy in urban areas. In terms of international climate agreements, the work aligns exceptionally well with the Paris Accord and the UN's 2030 Agenda for Sustainable Development (Yao & Zhang, 2022). Advocates of efficiency and resource management will view the model as a notable example, referring to it as the example of the city.

Human-Centric Approach

Integrating a human-centric approach into intelligent urban systems emphasizes prioritizing user needs, preferences, and convenience. This can be achieved through systematic collection of feedback from citizens, adapting services to meet their requirements, and leveraging personalization technologies such as artificial intelligence. Actively involving citizens in planning and management processes fosters greater engagement and trust in the systems while simultaneously enhancing the efficiency and effectiveness of decision-making.

Ethical Considerations

The ethical aspects of intelligent urban technologies encompass ensuring transparency, safeguarding personal data, and promoting equitable resource distribution. The deployment of IoT and AI requires adherence to stringent standards of cybersecurity and privacy while preventing discrimination or inequity in access to technological solutions. Developing a comprehensive ethical framework ensures that these technologies contribute to improving the quality of life for all citizens without compromising their security and fundamental rights.

CONCLUSION

Summary of Key Findings

This study presents a model for an adaptive ecosystem that integrates energy demand optimization and resource management in intelligent urban systems. The model demonstrates a significant improvement in energy efficiency. Two main factors contribute to this: First, a smart system allows the digital twinning study to reduce energy use by 15% during the most demanding peak times, such as between 5 and 8 PM, when people are typically home and using large amounts of energy. The model then assigns energy to the specific locations load zones on campus where it is needed, using a digital twin in real time to account for the number and location of people present. As for the emissions, the team's calculations show that the overall system is reducing them by 10 to 12 percent, with approximately half of that reduction attributed to the increased use of renewables. The system does not rely solely on solar energy, but when solar output is high, the real-time digital twin receives an ample supply of power, enabling it to perform all functions of its human counterpart, including significant peak shaving.

This model is particularly helpful because it aligns well with the vision of smart cities being developed globally. The smart grid and real-time data enable flexible decision-making in the management of urban resources. They also serve as workhorses in energy use and efficiency, which means they play a significant role in shaping our climate change future. This makes the smart grid and urban energy use a relevant topic for this book. The smart grid connects electricity consumption to urban resource efficiencies within a climate-impacted world. Additionally, the smart grid and integrated, real-time data function like driverless cars, heading towards flexible decision-making in urban resource management.

Future Perspectives

The upcoming research needs to be firmly rooted in an evaluation of the Smart and Sustainable City Model as it exists in the real-world variety of urban contexts. It needs to look at, and to some degree test, the model's applicability over a range of physical settings—urban physical settings that have, by their very nature, a diverse range of social, economic, and contextual factors. Doing so will allow the researchers to gain valuable insights into model's workings and into a clear assessment of its prospects for large-scale implementation across very different urban context.

REFERENCES

1. Adel, A. (2022). Future of industry 5.0 in society: human-centric solutions, challenges and prospective research areas. *Journal of Cloud Computing*, 11(1), 40.
2. Adel, A. (2023). Unlocking the future: fostering human–machine collaboration and driving intelligent automation through industry 5.0 in smart cities. *Smart Cities*, 6(5), 2742-2782.
3. Anagnostopoulos, T., Zaslavsky, A., Sosunova, I., Fedchenkov, P., Medvedev, A., Ntalianis, K., & Khoruznikov, S. (2018). A stochastic multi-agent system for Internet of Things-enabled waste management in smart cities. *Waste Management & Research*, 36(11), 1113-1121.
4. Binyamin, S. S., & Ben Slama, S. (2022). Multi-agent Systems for Resource Allocation and Scheduling in a smart grid. *Sensors*, 22(21), 8099.
5. Fraga-Lamas, P., Fernández-Caramés, T. M., da Cruz, A. M. R., & Lopes, S. I. (2024). An overview of blockchain for Industry 5.0: towards human-centric, sustainable and resilient applications. IEEE Access.
6. Ghobakhloo, M., Iranmanesh, M., Mubarak, M. F., Mubarik, M., Rejeb, A., & Nilashi, M. (2022). Identifying industry 5.0 contributions to sustainable development: A strategy roadmap for delivering sustainability values. Sustainable Production and Consumption, 33, 716-737.
7. Liu, Y., Yang, C., Jiang, L., Xie, S., & Zhang, Y. (2019). Intelligent edge computing for IoT-based energy management in smart cities. IEEE network, 33(2), 111-117.
8. Marinakis, V., & Doukas, H. (2018). An advanced IoT-based system for intelligent energy management in buildings. *Sensors*, 18(2), 610.
9. Mishra, P., & Singh, G. (2023). Energy management systems in sustainable smart cities based on the internet of energy: A technical review. *Energies*, 16(19), 6903.
10. Ordouei, M., Broumandnia, A., Banirostam, T., & Gilani, A. (2024). Efficient energy management in a smart city based on multi-agent systems over the Internet of Things platform. *International Journal of Nonlinear Analysis and Applications*, 15(11), 131-138.
11. Perera, A. T. D., & Kamalaruban, P. (2021). Applications of reinforcement learning in energy systems. *Renewable and Sustainable Energy Reviews*, 137, 110618.
12. Vasilev, I. (2024a). ADAPTIVE MODELS IN THE DISCOURSE OF TOMORROW'S TVET. *SCIENCE International Journal*, 3(3), 69–74. https://doi.org/10.35120/sciencej0303069v
13. Vasilev, I. (2024b). A Model of Design and Implementation Micro-credentials in TVET: A Promising and Flexible Pathway to Employment and Skill Development. *International Journal of Current Science Research and Review*. 07(12), [8807-8819] http://dx.doi.org/10.47191/ijcsrr/V7-i12-18
14. Vasilev, I. (2024c). The Model "SMART"- an Innovation for Achieving Future Success in TVET Students: An Empirical study. *International Journal of Current Science Research and Review*. 07(12), [8796-8806] http://dx.doi.org/10.47191/ijcsrr/V7-i12-17
15. Vasilev, I. (2024d). The T-Shaped Model: A Modern Paradigm for TVET Curriculum Design. Conceptual Framework, Theoretical Foundations and Practical Examples. *International Journal of Current Science Research and Review*. 7(11), [8293-8305]. http://dx.doi.org/10.47191/ijcsrr/v7-i11-17
16. Vasilev, I. (2024e). Synergetic Approach Model for Improving Vocational Education: Characteristics, Guidelines and Applications. *International Journal of Current Science Research and Review*, Vol 7. No 9. pp.7261-7267
17. Vasilev, I. (2024f). The Meta-Subject Model: A Holistic Framework Overcoming the Limitations of Subject-Based Learning with an Example in TVET. *International Journal of Current Science Research and Review*, 7(10), [8077-8090]. https://doi.org/10.47191/ijcsrr/V7-i10-69
18. Vasilev, I. (2024g). SMART CITY AND THE MODEL OF VOCATIONAL EDUCATION AND TRAINING: NEW TRENDS, ADVANTAGES AND CHALLENGES. *KNOWLEDGE - International Journal*, 65(5), 529–535.
19. Vasilev, I. (2024h). MODEL "LOOSE" OR PROJECT FOR DIFFERENTIATION OF LEARNING PATHWAYS IN VOCATIONAL EDUCATION WITH PRACTICAL EXAMPLE. *KNOWLEDGE - International Journal*, 66(2), 223–228. Retrieved from https://ikm.mk/ojs/index.php/kij/article/view/7021

20. Silva, B. N., Khan, M., & Han, K. (2018). Towards sustainable smart cities: A review of trends, architectures, components, and open challenges in smart cities. *Sustainable cities and society*, 38, 697-713.
21. Sima, V., Gheorghe, I. G., Subić, J., & Nancu, D. (2020). Influences of the industry 4.0 revolution on the human capital development and consumer behavior: A systematic review. Sustainability, 12(10), 4035.
22. Yang, J., Liu, Y., & Morgan, P. L. (2024). *Human-machine interaction towards Industry 5.0: Human-centric smart manufacturing.* Digital Engineering, 100013.
23. Yao, Q., & Zhang, H. (2022). Improving agricultural product traceability using blockchain. *Sensors*, 22(9), 3388.
24. Mulla, R. (n.d.). Hourly Energy Consumption: Over 10 years of hourly energy consumption data from PJM in megawatts. Kaggle. Retrieved [20/12/2024], from https://www.kaggle.com/datasets/robikscube/hourly-energy-consumption/discussion?sort=hotness.