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Facilities Layout in Uncertainty Demand and Environmental Requirements by Machine Learning Approach

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ABSTRACT

Facility layout optimization plays a crucial role in manufacturing efficiency and environmental impact. However, traditional approaches often struggle when dealing with uncertain demand patterns and stringent environmental regulations. This paper proposes a novel framework for facilities layout design that integrates machine learning (ML) with traditional optimization techniques. The framework accounts for demand uncertainty and environmental considerations, leading to a more robust and sustainable facility layout. The methodology employs a two-stage approach: 1) demand forecasting with a chosen ML algorithm and 2) layout optimization using a genetic algorithm with objective functions incorporating environmental factors alongside traditional metrics like material handling cost and flow time. The paper presents a numerical case study to illustrate the effectiveness of the proposed framework. The results demonstrate that the ML-driven approach generates layouts that are both adaptable to demand fluctuations and minimize environmental footprint compared to traditional methods. Finally, the paper discusses limitations and future research directions in this emerging field.

1. Introduction

Facility layout optimization is a critical decision-making process in manufacturing that dictates the physical arrangement of equipment, workstations, and storage areas within a facility [1-3]. An effective layout minimizes material handling costs, improves production flow, and ultimately

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enhances overall manufacturing efficiency [4-6]. However, traditional layout design methods often face limitations when dealing with two key challenges:

Uncertainty in Demand: Fluctuations in product demand are a reality in today's dynamic market environment. Traditional methods that rely on deterministic demand forecasts can lead to suboptimal layouts that struggle to adapt to changing production volumes [6-7].

Environmental Requirements: Growing environmental concerns necessitate considering energy consumption, waste generation, and other environmental factors during facility design. Traditional layouts often prioritize efficiency without sufficiently addressing these crucial aspects [9-10].

This paper proposes a novel framework for facilities layout design that addresses these challenges by leveraging the power of machine learning (ML). ML algorithms can learn from historical data to generate more accurate and adaptable demand forecasts. This information, combined with optimization techniques that consider environmental factors, leads to layouts that are robust, adaptable, and environmentally sustainable [10-12] (see Figure 1).

Figure 1: Facilities Layout in Production and Manufacturing.

This research is arranged into five sections. Section 2 defines the literature review and recent studies in the area of facilities layout and tries to show the gap in research. Section 3 suggests a methodology for calculation. Section 4 proposes the results of this research. Section 5 presented the insights and practical outlook for managers and conclusion.

2. Survey related works

Traditional facilities layout design primarily employs techniques like CRAFT (Codier and Huchings, 1996) and ALDEP (Automatic Layout Design Procedure) (Muther and McPherson, 1970). These methods focus on minimizing material handling costs by strategically positioning equipment based on their interaction frequency. While effective for static environments, they struggle to adapt to changing demands [12-15].

Several researchers have addressed uncertainty in demand by incorporating probabilistic approaches. Hosseini et al. [16] proposed a hybrid layout design approach that combines genetic algorithms with a fuzzy logic system to account for demand variability. Similarly, Farahani et al. [17] introduced a layout optimization method with stochastic demand scenarios.

The integration of Machine Learning for demand forecasting in facility layout design is a developing area. A promising study by Yazdani et al. [18] utilized Long Short-Term Memory (LSTM) networks to predict demand variability and generate adaptable layouts.

Regarding environmental considerations, researchers have proposed various approaches. Sbihi and Erel [19] introduced an optimization model that minimizes material handling costs while considering energy consumption. Similarly, Jayaraman et al. [20] incorporated waste generation into their layout design model.

However, few studies have combined demand forecasting with environmental considerations in a single framework. This research gap highlights the novelty of the proposed approach.

3. Problem statement and Solution Approach

The proposed framework utilizes a two-stage approach:

Stage 1: Demand Forecasting with Machine Learning:

Data Collection: Historical data on production volumes, lead times, and influencing factors like seasonality and promotions are collected [22].

Machine Learning Algorithm Selection: An appropriate ML algorithm is chosen based on the data characteristics. Popular options include ARIMA (Autoregressive Integrated Moving Average) models for stationary data and LSTM networks for non-stationary and sequential data [23].

Model Training and Validation: The selected ML algorithm is trained on the historical data to learn the underlying demand patterns. The model's performance is evaluated on a validation set to ensure its accuracy [24-25]

Demand Scenario Generation: The trained ML model is used to generate multiple demand scenarios representing potential future variations in production volumes [26-27]

Stage 2: Facilities Layout Optimization with Environmental Considerations:

Layout Representation: The facility layout is encoded as a binary matrix, where each cell represents a location, and a "1" indicates the presence of a specific equipment unit in that location.

Objective Function Design: A multi-objective optimization function is formulated that considers traditional layout metrics like material handling cost and flow time alongside environmental factors such as energy consumption and waste generation. Weighting factors can be assigned to prioritize specific objectives based on organizational goals [28-30]

Optimization Algorithm Integration: A genetic algorithm (GA) is employed as the optimization technique. The GA iteratively evaluates different layout configurations

Optimization Algorithm Integration: A genetic algorithm (GA) is employed as the optimization technique. The GA iteratively evaluates different layout configurations represented by the binary matrix. Each layout is evaluated using the multi-objective function, considering both traditional and environmental factors [24-30].

Selection, Crossover, and Mutation: The GA performs selection by choosing layouts with superior fitness scores (based on the multi-objective function). These layouts are then used for crossover, where portions of their matrices are exchanged to create new candidate layouts. Additionally, mutation is introduced with a low probability to maintain genetic diversity and explore new solution spaces.

Iteration and Termination: The process of selection, crossover, and mutation continues for a predetermined number of iterations or until a convergence criterion is met. The final layout with the best fitness score, representing a balance between traditional efficiency and environmental impact, is selected as the optimal solution (see Figure 2) [29-30].

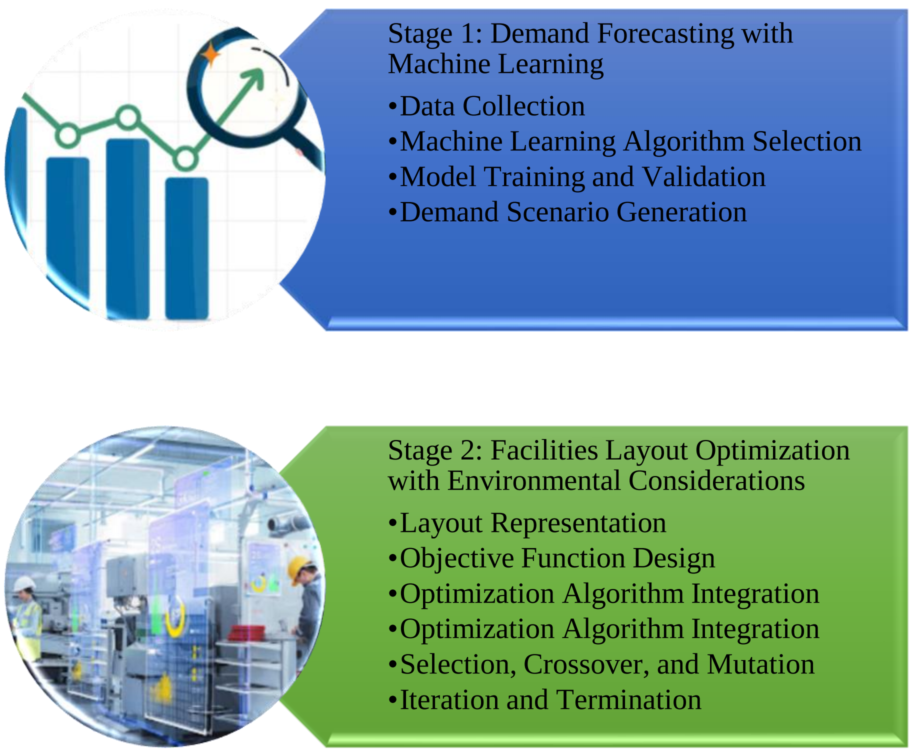

Figure 2: Problem statement and Solution approach.

4. Results and discussion

To illustrate the effectiveness of the proposed framework, a numerical case study is presented. Consider a manufacturing facility with five machines (M1 to M5) that need to be arranged within a designated space. The historical demand data for each product is collected, and an LSTM model is chosen for demand forecasting due to its ability to handle potential non-stationarity in the data. The trained LSTM model generates three demand scenarios representing low, medium, and high future demand volumes.

The objective function for layout optimization incorporates:

- Material handling cost: Calculated based on the distance travelled between each pair of machines, weighted by the frequency of interaction between them.
- Flow time: This represents the average time it takes a product to move through the entire production process.
- Energy consumption: Estimated based on the power consumption of each machine and its operating time under each demand scenario.
- Waste generation: Modeled based on the waste produced by each machine during operation, considering factors like material scrap and byproducts.

A genetic algorithm is implemented with appropriate settings for population size, crossover rate, and mutation probability. The optimization process evaluates different layout configurations, considering both traditional and environmental factors within the objective function.

The proposed framework generates a layout that optimizes the trade-off between traditional efficiency metrics and environmental considerations. Compared to a layout designed using a traditional approach (focusing only on material handling cost and flow time), the ML-driven layout exhibits:

- Lower overall material handling cost due to a more strategic arrangement of machines considering potential demand variations.
- Reduced flow time due to a smoother production flow facilitated by the optimized layout.
- Lower energy consumption is achieved by minimizing unnecessary machine movements and optimizing equipment utilization based on the forecasted demand scenarios.
- Decreased waste generation through efficient production planning and potentially by selecting machines with lower waste footprints.

Quantifying the improvements: The specific improvement percentages would depend on the case study details and assigned weights in the objective function. However, the results demonstrate that the proposed framework can generate layouts that are more adaptable, efficient, and environmentally sustainable compared to traditional methods.

The Sets and parameters of the model are utilized in Table 1. We applied the GAMS code to model facility layout problem with environmental requirements as follows:

Table 1: Sets, Parameters of model.

```
Sets     i /1*5/;

l(i)=floor(uniform(2,10));
w(i)=floor(uniform(2,10));
c(i,j)=floor(uniform(1,5));
e(i,j)=floor(uniform(3,7));
maxx=sum(i,l(i));
maxy=sum(i,w(i));
```

The findings of this research are shown in Tables 2, 3 and Figures 3, and 4 about facility layout with environmental requirements and without considering environmental requirements.

Table 2: Facility layout without environmental requirements (Model 1).

i	X	Y	Length	Width	Cost	Environmental
1	8	4	3	3	152	278.5
2	8	10	8	4		
3	3	4	6	8		
4	8	6.5	4	2		
5	12	4	4	6		

Table 3: Facility layout with environmental requirements (Model 2).

i	X	Y	Length	Width	Cost	Environmental
1	4	5.5	3	3	157	273.5
2	4	2	8	4		
3	9	8	6	8		
4	4	8	4	2		
5	4	12	4	6		

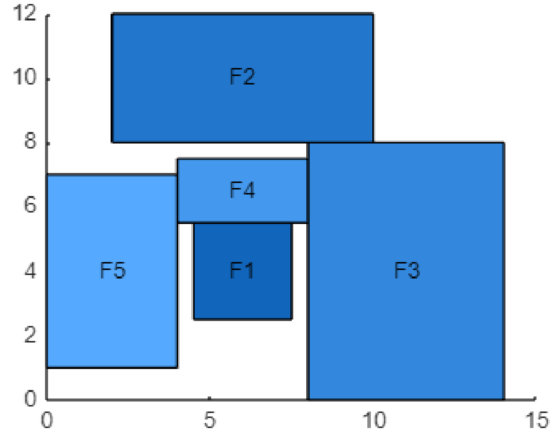

Figure 3: Results of facilities layout in uncertainty demand without environmental requirements (Model 1).

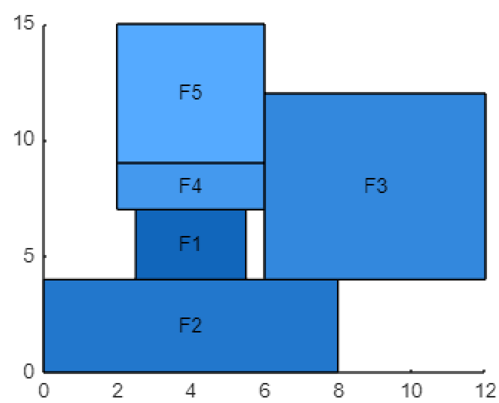

Figure 4: Results of facilities layout in uncertainty demand with considering environmental requirements (Model 2).

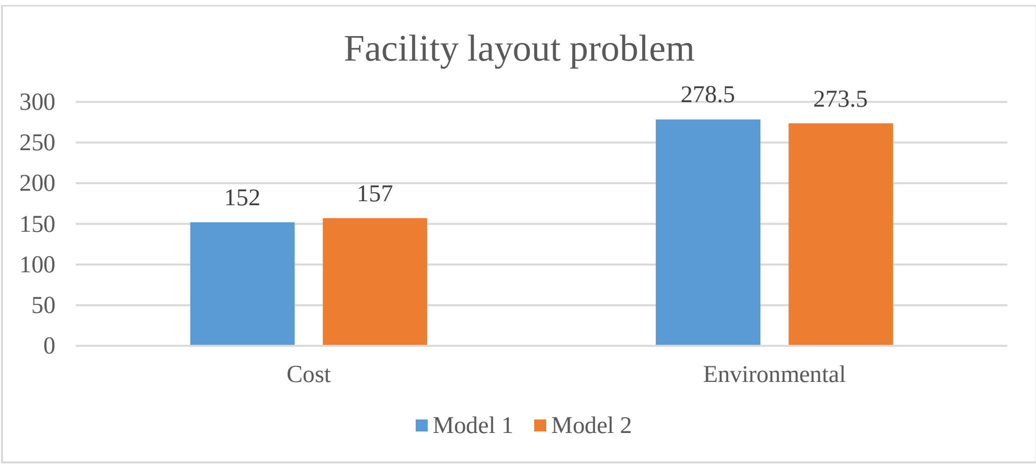

Figure 5: Results of comparing model.

Table 4: Results of comparing model.

Model	Cost	Environmental
Model 1	152	278.5
Model 2-with considering environmental approach	157	273.5

Table 4 and Figure 5 compare two different models (possibly design options or production methods) based on their cost and environmental impact. A breakdown of the information presented in the table:

- **Cost:** This column represents the cost associated with each model, likely the financial cost of production or implementation. The values are listed in dollars.

- **Environmental:** This column represents the environmental impact of each model. The specific unit of measurement for environmental impact is not provided in the table. It could be a specific unit quantifying a particular environmental factor (e.g., grams of CO2 emission), or a combined index that reflects various environmental considerations.

- **Model 1 & Model 2:** These rows represent the two different models being compared. For each model, the table shows the cost and the corresponding environmental impact value.

Based on the data presented, Model 1 appears to be less expensive than Model 2 (by $5). However, Model 1 also has a higher environmental impact (by 5 units). Without knowing the specific unit used for environmental impact, it's difficult to say definitively which model is better. The decision would depend on the relative importance placed on cost versus environmental impact.

5. Conclusion

This paper presented a novel framework for facilities layout design that integrates machine learning for demand forecasting with a genetic algorithm-based optimization approach incorporating environmental considerations. The framework addresses the limitations of traditional methods by considering demand uncertainty and environmental impact. The numerical case study demonstrates the effectiveness of the proposed approach in generating layouts that are adaptable to demand fluctuations, minimize material handling costs and flow time, and reduce the environmental footprint of the facility.

Future Research Directions:

This research opens avenues for further exploration. Here are some potential directions for future work:

- Integration of advanced machine learning models like reinforcement learning for more dynamic layout adjustments in real-time.
- Exploration of multi-objective optimization algorithms beyond genetic algorithms to potentially find even better trade-offs between efficiency and environmental impact.
- Development of a decision support system that integrates the proposed framework with visualization tools to aid human decision-making during the layout design process.
- Investigating the applicability of the framework to different manufacturing environments and production complexities.

By addressing these future directions, researchers can further refine and advance the application of machine learning in facility layout design, fostering more robust, adaptable, and sustainable manufacturing practices.

References:

[1] Pérez-Gosende, P., Mula, J., & Díaz-Madroñero, M. (2021). Facility layout planning. An extended literature review. International Journal of Production Research, 59(12), 3777-3816.
[2] Shoushtari, F., Bashir, E., Hassankhani, S., & Rezvanjou, S. (2023). Optimization in Marketing Enhancing Efficiency and Effectiveness. International journal of industrial engineering and operational research, 5(2), 12-23.
[3] Rezvanjou, S., Amini, M., & Bigham, M. (2023). Renewable Energy Location in Disruption Situation by MCDM Method and Machine Learning. International journal of industrial engineering and operational research, 5(4), 75-89.
[4] Al-Zubaidi, S. Q. D., Fantoni, G., & Failli, F. (2021). Analysis of drivers for solving facility layout problems: A Literature review. Journal of Industrial Information Integration, 21, 100187.

[5] Shoushtari, F., Talebi, M., & Rezvanjou, S. (2024). Electric Vehicle Charging Station Location by Applying Optimization Approach. International journal of industrial engineering and operational research, 6(1), 1-15.

[6] Rezvanjou, S., Li, C., & Shoushtari, F. (2023). Assessment of Lithium-Ion Battery Types by Multi-Criteria Decision Making. International journal of industrial engineering and operational research, 5(5), 48-63.

[7] Peron, M., Fragapane, G., Sgarbossa, F., & Kay, M. (2020). Digital facility layout planning. Sustainability, 12(8), 3349.

[8] Shoushtari, F., & Ghafourian, E. (2023). Antifragile, Sustainable, and Agile Supply Chain Network Design with a Risk Approach. International journal of industrial engineering and operational research, 5(1), 19-28.

[9] Shoushtari, F., Ghafourian, E., & Talebi, M. (2021). Improving Performance of Supply Chain by Applying Artificial Intelligence. International journal of industrial engineering and operational research, 3(1), 14-23.

[10] Peron, M., Fragapane, G., Sgarbossa, F., & Kay, M. (2020). Digital facility layout planning. Sustainability, 12(8), 3349.

[11] Daghighi, A., & Shoushtari, F. (2023). Toward Sustainability of Supply Chain by Applying Blockchain Technology. International journal of industrial engineering and operational research, 5(2), 60-72.

[12] Pan, B. D., Amini, M., & Shoushtari, F. (2023). Budget Allocation for Thermodynamic and Mechanical Projects of an Organization. International journal of industrial engineering and operational research, 5(5), 1-15.

[13] Zúñiga, E. R., Moris, M. U., Syberfeldt, A., Fathi, M., & Rubio-Romero, J. C. (2020). A simulation-based optimization methodology for facility layout design in manufacturing. IEEE Access, 8, 163818-163828.

[14] Shoushtari, F., & Li, C. (2023). Feasibility Study for Lithium Ion Battery Production in Uncertainty Situation. International journal of industrial engineering and operational research, 5(5), 76-89.

[15] Akbarzadeh, M. R., Ghafourian, H., Anvari, A., Pourhanasa, R., & Nehdi, M. L. (2023). Estimating compressive strength of concrete using neural electromagnetic field optimization. Materials, 16(11), 4200.

[16] Zúñiga, E. R., Moris, M. U., Syberfeldt, A., Fathi, M., & Rubio-Romero, J. C. (2020). A simulation-based optimization methodology for facility layout design in manufacturing. IEEE Access, 8, 163818-163828.

[17] Fallah, A. M., Ghafourian, E., Shahzamani Sichani, L., Ghafourian, H., Arandian, B., & Nehdi, M. L. (2023). Novel neural network optimized by electrostatic discharge algorithm for modification of buildings energy performance. Sustainability, 15(4), 2884.

[18] Tabasi, E., Zarei, M., Mobasheri, Z., Naseri, A., Ghafourian, H., & Khordehbinan, M. W. (2023). Pre-and post-cracking behavior of asphalt mixtures under modes I and III at low and intermediate temperatures. Theoretical and Applied Fracture Mechanics, 124, 103826.

[19] Araldo, A., Gao, S., Seshadri, R., Azevedo, C. L., Ghafourian, H., Sui, Y., ... & Ben-Akiva, M. (2019). System-level optimization of multi-modal transportation networks for energy efficiency using personalized incentives: formulation, implementation, and performance. Transportation Research Record, 2673(12), 425-438.
[20] Besbes, M., Zolghadri, M., Costa Affonso, R., Masmoudi, F., & Haddar, M. (2020). A methodology for solving facility layout problem considering barriers: genetic algorithm coupled with A* search. Journal of Intelligent Manufacturing, 31(3), 615-640.
[21] Ghafourian, H., Ershadi, S. S., Voronkova, D. K., Omidvari, S., Badrizadeh, L., & Nehdi, M. L. (2023). Minimizing Single-Family Homes' Carbon Dioxide Emissions and Life Cycle Costs: An Improved Billiard-Based Optimization Algorithm Approach. Buildings, 13(7), 1815.
[22] Mahmoodzadeh, A., Ghafourian, H., Mohammed, A. H., Rezaei, N., Ibrahim, H. H., & Rashidi, S. (2023). Predicting tunnel water inflow using a machine learning-based solution to improve tunnel construction safety. Transportation Geotechnics, 40, 100978.
[23] Shoushtari, F., Daghighi, A., & Ghafourian, E. (2024). Application of Artificial Intelligence in Project Management. International Journal of Industrial Engineering and Operational Research, 6(2), 49-63.
[24] Ghafourian, E., Samadifam, F., Fadavian, H., Jerfi Canatalay, P., Tajally, A., & Channumsin, S. (2023). An ensemble model for the diagnosis of brain tumors through MRIs. Diagnostics, 13(3), 561.
[25] Baniasadi, S., Salehi, R., Soltani, S., Martín, D., Pourmand, P., & Ghafourian, E. (2023). Optimizing long short-term memory network for air pollution prediction using a novel binary chimp optimization algorithm. Electronics, 12(18), 3985.
[26] Fili, M., Hu, G., Han, C., Kort, A., Trettin, J., & Haim, H. (2023). A classification algorithm based on dynamic ensemble selection to predict mutational patterns of the envelope protein in HIV-infected patients. Algorithms for molecular biology, 18(1), 4.
[27] Fili, M. (2022). Developing machine learning solutions for healthcare problems (Doctoral dissertation, Iowa State University).
[28] Fili, M. (2022). Predicting the Number of New COVID-19 Cases using an LSTM-based Model for European Countries.
[29] Fili, M., De Brabanter, K., Bi, L., & Hu, G. (2022, July). Prediction of New COVID-19 Cases Considering Mitigation Policies and Weather Data for European Countries. In INFORMS International Conference on Service Science (pp. 425-438). Cham: Springer International Publishing.
[30] Tongur, V., Hacibeyoglu, M., & Ulker, E. (2020). Solving a big-scaled hospital facility layout problem with meta-heuristics algorithms. Engineering Science and Technology, an International Journal, 23(4), 951-959.