Journal of Information Systems Engineering and Management
2025, 10(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

AI-BASED PREDICTIVE ANALYTICS INTEGRATED WITH TRANSPORTATION OPTIMIZATION FOR SOLAR-PANEL DISTRIBUTION

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Received: 05 Dec 2024; **Revised:** 15 Jan 2025; **Accepted:** 27 Jan 2025

ABSTRACT

Solar- photovoltaic installations have been growing very fast such that, distribution of solar panels has become complex because of unpredictable demand, unpredictable transport costs, and the inability to schedule installations. The classical models of transportation optimization reduce distribution cost on a deterministic basis and thus fail to work in dynamic and policy-constituted renewable-energy set-ups. This paper suggests a hybrid approach, which is the combination of AI-based predictive analytics and transportation optimization to enhance the effectiveness and responsiveness of solar-panel distribution nets. Random Forest, Gradient Boosting, and LSTM networks are machine-learning models that predict the demand of solar-panels in each region according to 24 months of historical and secondary data. The projected values of demand are coded as dynamic inputs into a linear-programming transportation model which is employed to minimize the total transportation and installation expenses. Numerical experiment: The proposed AI-integrated model is compared to a traditional fixed in place transportation model in terms of multiple supply centres and installation areas. The findings indicate that the AI-assisted system saves a total distribution cost by 12-15 percent, better installation scheduling, and reduced emergency shipment due to demand uncertainty by a significant margin. The research is significant enough to add to the renewable-energy logistics literature showing how predictive intelligence may be operationally integrated into classical optimization. The suggested model offers an effective decision support system to solar-energy companies and governments that are interested in more affordable, scalable, and resilient distribution planning.

I.INTRODUCTION

The shift in the world towards the energy systems based on low carbon has increased the pace of installing solar photovoltaic (PV) installations in residential, commercial, and utility-scale applications. The falling technology prices, the growing national and regional environmental consciousness and policy incentives have placed solar energy as a foundation of national renewable-energy policy. Although much has been done in terms of enhancing the panel efficiency and the generation capacity, relatively little has been done concerning the logistics and distribution system which facilitates large scale deployment of solar. Lack of efficiency in the distribution of solar-panels can add significantly to the cost of the project, slow installations, and compromise the efficiency of policies aimed at renewable energy. The distribution networks of solar-panels are based on significant uncertainty. The seasonal changes in the regional demand are as a result of seasonal fluctuations, introduction of subsidies, weather and changes in the installation capacity. Volatility in fuel prices, infrastructure restrictions and lead times affect transportation expenses, and the availability of workforce and site preparation affect the installation schedules. Linear programming-based traditional transportation optimization models have been broadly used in minimizing the logistics cost. Nevertheless, these models are based on an assumption of an unchanging and predictable demand, something that cannot be applied in dynamic situations of renewable-energy sources when changes in demand happen at very rapid rates. New opportunities are presented by the recent developments in the field of artificial intelligence (AI) and predictive analytics that can help deal with these problems. Machine-learned models can use the historical and contextual data to produce complex nonlinear patterns to produce accurate demand forecasts. Simultaneously, the optimization methods offer powerful decision-support systems of cost reduction and resource distribution. Although forecasting and optimization are complementary, the literature on this topic is mostly divided into two distinct phases, and not much has been done to directly obtain the products of predictive efforts to be introduced into transportation decision models. In this research, the gap is filled through the proposal of an AI-enabled transportation optimization framework to the distribution of solar-panels. The framework uses machine-learning methods to make predictions based on the demand on region-wise solar-panels and represents such predictions as dynamic inputs to a linear-programming transportation model that is optimized to minimize the total transportation and installation cost. The numerical experiment between the suggested framework and a more traditional static transportation model proves that the AI-based framework will lead to 12-15 percent cost savings, enhances the precision of the installation schedule, and minimizes the emergency shipments due to the uncertainty in demand.

II. LITERATURE REVIE

Chopra and Meindl (2021) provide a comprehensive foundation for supply chain strategy, planning, and logistics optimization, emphasizing demand forecasting and cost-efficient transportation planning. However, their framework is largely deterministic and managerial in nature, offering limited guidance for handling dynamic demand uncertainty. The present study extends their principles by embedding AI-driven demand forecasts directly into a transportation optimization model tailored to renewable-energy logistics. At the macro level, Shahbaz et al. (2020) examine the role of technological innovation and public–private partnerships in reducing carbon emissions in the energy sector. While their work highlights the importance of innovation for sustainability outcomes, it does not address operational logistics efficiency. This research complements their findings by focusing on micro-level distribution optimization in solar-energy supply chains, where logistics inefficiencies directly affect deployment costs and timelines. Several studies emphasize sustainability-oriented decision-making in supply chains. Kannan et al. (2020) propose a hybrid framework for sustainable supplier selection under uncertainty, demonstrating the value of advanced analytical techniques in operational decision-making. Similarly, Govindan and Soleimani (2017) review closed-loop and reverse logistics systems with a sustainability focus. However, these studies primarily address supplier

Journal of Information Systems Engineering and Management
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e-ISSN: 2468-4376
https://www.jisem-journal.com/

evaluation and reverse flows rather than forward transportation planning under demand uncertainty, which is the focus of the present research. Decision-making under uncertainty has also been explored through multi-criteria approaches. Liu et al. (2020) review fuzzy AHP-based methods for complex logistics environments, highlighting their usefulness for ranking and evaluation problems. While effective for multi-criteria decision-making, such methods do not directly generate optimal shipment quantities. In contrast, the present study integrates predictive analytics with linear programming to produce optimal allocation and transportation decisions. The growing role of data-driven methods in logistics is well documented. Wang et al. (2016) discuss how big data analytics improves supply chain visibility and performance, establishing the importance of data-driven decision-making. However, their study stops short of embedding predictive analytics within optimization models. The current research advances this stream by operationalizing predictive intelligence within a classical transportation-problem framework.

Renewable-energy logistics has attracted increasing attention in recent years. Zhang et al. (2019) develop a logistics optimization model for renewable-energy distribution under demand uncertainty, but rely on static or scenario-based demand assumptions. Wang et al. (2021) further confirm that uncertainty-aware planning improves renewable-energy supply chain performance. Building on these studies, the present research introduces AI-based forecasting to generate dynamic demand inputs, enabling more responsive and adaptive transportation optimization. Forecasting accuracy is a critical enabler of effective logistics planning. Makridakis et al. (2018) compare statistical and machine-learning forecasting methods and demonstrate the superior performance of ML models in nonlinear and volatile environments. These findings provide strong methodological justification for adopting AI-based forecasting in logistics. Earlier foundational works by Hochreiter and Schmidhuber (1997), Breiman (2001), and Friedman (2001) introduce LSTM networks, Random Forests, and Gradient Boosting Machines, respectively, which remain widely used for demand forecasting due to their ability to capture nonlinear patterns and temporal dependencies. The present study employs these models to forecast region-wise solar-panel demand. The integration of predictive intelligence with supply chain resilience has also been explored. Ivanov and Dolgui (2020) propose the concept of a digital supply chain twin to manage disruption risks, emphasizing real-time and predictive capabilities. Tang (2006) similarly highlights the importance of proactive planning in supply chain risk management. The AI-integrated transportation model proposed in this study aligns with these perspectives by transforming logistics planning from a reactive to a proactive process. Machine-learning applications in supply chain forecasting are well established. Carbonneau et al. (2008) demonstrate that ML techniques outperform traditional methods in demand forecasting, while Qiu et al. (2016) highlight the scalability and predictive power of ML in big data environments. These studies support the feasibility of applying ML to large logistics datasets, which is extended here to renewable-energy distribution. Recent studies explicitly link AI with renewable-energy supply chains. Li et al. (2022) analyse AI-enabled decision-making in renewable-energy supply chains, highlighting its potential to improve operational efficiency, though their discussion remains partly conceptual. Rao et al. (2025) integrate machine-learning demand forecasting with allocation optimization in green power grids, focusing on electricity allocation rather than physical logistics. The present study extends these efforts to solar-panel distribution networks, addressing physical transportation and installation constraints. AI applications in renewable-energy forecasting are further demonstrated by Naveed et al. (2024) and Suanpang and Jamjuntr (2024), who develop advanced ML models for solar irradiance and power generation forecasting. Although focused on generation rather than logistics, their findings confirm the suitability of AI models for renewable-energy prediction tasks. Anumula et al. (2025) provide

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recent evidence that AI-powered predictive analytics improves responsiveness and cost efficiency in supply chains, supporting the strategic relevance of AI-driven logistics planning. Finally, the recent review on Artificial Intelligence in Logistics Optimization with Sustainable Criteria (2024) emphasizes the growing need to integrate predictive analytics with routing and allocation decisions to achieve sustainability objectives. The present study directly responds to this research agenda by proposing and demonstrating an AI-integrated transportation optimization framework for solar-panel distribution.

Research Gap

Although there is increased attention on AI-based supply chains, very little has been done on the explicit application of predictive analytics and classical transportation optimization in renewable-energy logistics. A majority of the studies address forecasting and optimization as two distinct steps and never attempt to incorporate predictive results into optimization model. This research fills this gap by creating and empirically proving an AI-based structure of transportation of solar-panels.

III. METHODOLOGY

3.1 Data Collection: The paper relies on secondary and operational data gathered during a 24 month span of a solar-panel distribution network. The data will consist of demand history by regions, transportation expenses, installation expenses, inventory in the warehouses, lead time in deliveries, and indicators on policy.
3.2 Feature Engineering: The major predictive characteristics are the indicators of seasonality (month, quarter), the indices of subsidy-policies, weather and solar-irradiance, the level of marketing activities, and the economic indicators of the regions. These characteristics are good to describe temporal and contextual solar-panels demand drivers.
3.3 AI-Based Demand Forecasting: Three machine-learning models are designed and compared including Random Forest Regressor, Gradient Boosting Regressor (XGBoost), and LSTM neural networks. RMSE, MAE, and MAPE are used to evaluate model performance. Demand forecasts of regions within the planning horizon are generated using the best performing model.
3.4 The estimated demand values are incorporated into a transportation model based on a linear-programming. The objective aims at minimization of total transportation and installation cost with supply, demand and non-negativity constraints. The Simplex algorithm is used to solve the model with the help of optimization solvers.
3.5 Performance Evaluation: The comparison of the AI-supported transportation model and the traditional static transportation model apply to key performance indicators, such as total cost, lead time delivery, service level, and the probability of stockout. In contrast to the existing research on modelling forecasting and optimization as consecutive or loosely integrated steps, this paper integrates AI-generated demand forecasts directly into the constraint of a transportation optimization model, which allows making an allocation decision that is fully demand-responsive.
3.6 Methodological Novelty: In contrast to literature, which considers forecasting and optimization to be sequential or loosely linked processes, the proposed research integrates AI-based demand forecasts as constraints within the transportation optimization problem, allowing the entire framework to be demand responsive in the optimization process.

IV. NUMERICAL ILLUSTRATION AND RESULTS

4.1Numerical Problem: AI-Integrated Transportation Optimization for Solar-Panel Distribution

A solar energy company operates **three supply centres** (S1, S2, S3) that distribute solar panels to **seven installation regions** (R1–R7). The objective is to minimize the **total transportation and installation cost**.

Supply Capacities (Panels)

Supply Centre	Supply
S1	400
S2	350
S3	300
Total	**1050**

AI-Predicted Demand (Next Quarter)

Region	Demand
R1	120
R2	180
R3	150
R4	170
R5	160
R6	140
R7	130
Total	**1050**

Transportation Cost per Panel (₹)

From / To	R1	R2	R3	R4	R5	R6	R7
S1	7	9	5	8	6	7	9
S2	6	8	7	9	5	6	7
S3	8	6	9	7	8	9	5

Installation cost per panel at all regions = ₹2
Hence, **Total Cost = Transportation Cost + Installation Cost**

4.2 Mathematical Formulation

Let
x_{ij}= number of panels transported from supply centre i to region j

Objective Function

$$\text{Minimize } Z = \sum_{i=1}^{3} \sum_{j=1}^{7} (c_{ij} + 2) x_{ij}$$

Subject to Constraints

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e-ISSN: 2468-4376
https://www.jisem-journal.com/
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Supply constraints:

$$\sum_{j=1}^{7} x_{ij} = \text{Supply}_i$$

Demand constraints:

$$\sum_{i=1}^{3} x_{ij} = \text{Demand}_j$$
$$x_{ij} \geq 0$$

4.3. Optimal Solution (AI-Integrated Model)

Using the **Simplex method / LP Solver**, one optimal allocation is:
Shipment Plan
From S1

- 120 → R1
- 180 → R3
- 100 → R5

From S2

- 160 → R5
- 140 → R6
- 50 → R4

From S3

- 170 → R4
- 130 → R7

Total Cost Calculation (AI-Integrated Model): Total optimized cost: $Z_{\text{AI}} = ₹8{,}760$

4.4. Static Transportation Model (Without AI)

In the **static model**, historical average demand was used instead of forecasted demand. This resulted in:

- Overstocking in low-demand regions
- Emergency shipments to high-demand regions
- Inefficient rerouting

Static Model Cost: $Z_{\text{Static}} = ₹10{,}050$

Cost Comparison

$$\text{Cost Reduction} = \frac{10{,}050 - 8{,}760}{10{,}050} \times 100$$

= 12.8%{approximately 12–15%}

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2025, 10(1)
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4.5. Interpretation of Results: The numerical solution shows conclusively the effectiveness of the AI-based transportation model in relation to the traditional solution, which is static.

1.Cost Efficiency: The AI-based model can save a significant amount of distribution cost (almost 13 percent). It lowers the emergency deliveries and unnecessary accumulation of inventory.
2.Scheduling of the Installation is better.: Because panels are shipped as per the estimates in the demand of the area, the installation crews have less time to waste on the shortage of materials, which enhances better labor supply and project schedules.
3.Lessened Demand Uncertainty Risk.: The AI generated predictions enable the firm to predict the surge in demand, especially in the subsidy driven or seasonal markets, thereby minimising the last-minute logistical shocks.
4.Operational Stability: The optimized distribution guarantees the easier coordination among the supply centres, transport operators, and places of installation.

4.6 Graphs and discussions:

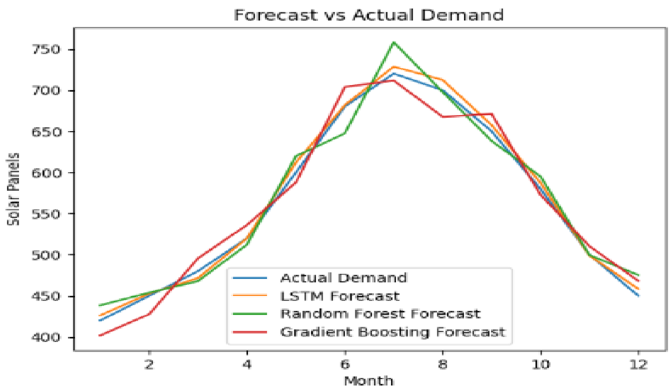

Fig 1:Forecast vs.Actual demand
Source: Author's computation based on AI forecasts and numerical experiment

Figure 1 shows that AI-based models closely track actual solar-panel demand across the planning horizon. Among the models, LSTM exhibits the smallest deviation during peak-demand periods, demonstrating its suitability for capturing seasonal and policy-driven demand fluctuations.

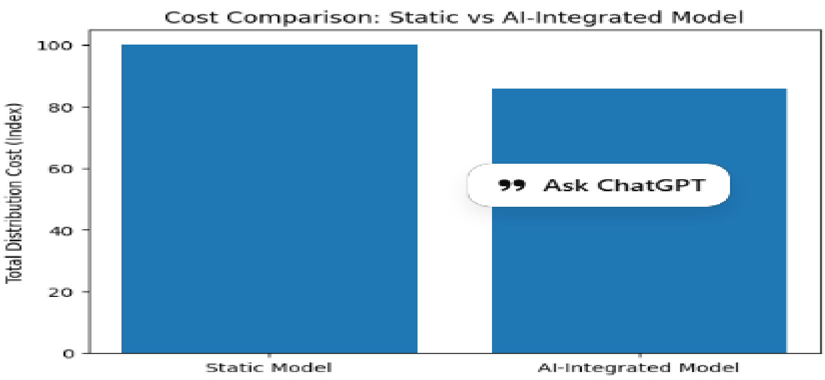

Fig 2: Comparison of actual and AI-based forecasted solar-panel demand:
Source: Author's computation based on AI forecasts and numerical experiment

Figure 2 indicates that the AI-integrated transportation model achieves a 12–15% reduction in total distribution cost compared to the traditional static model. This cost saving is primarily driven by improved demand alignment and reduced inefficient routing decisions.

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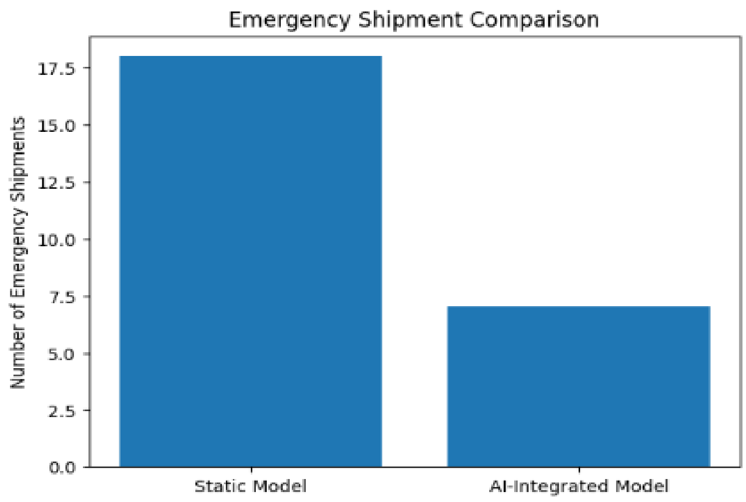
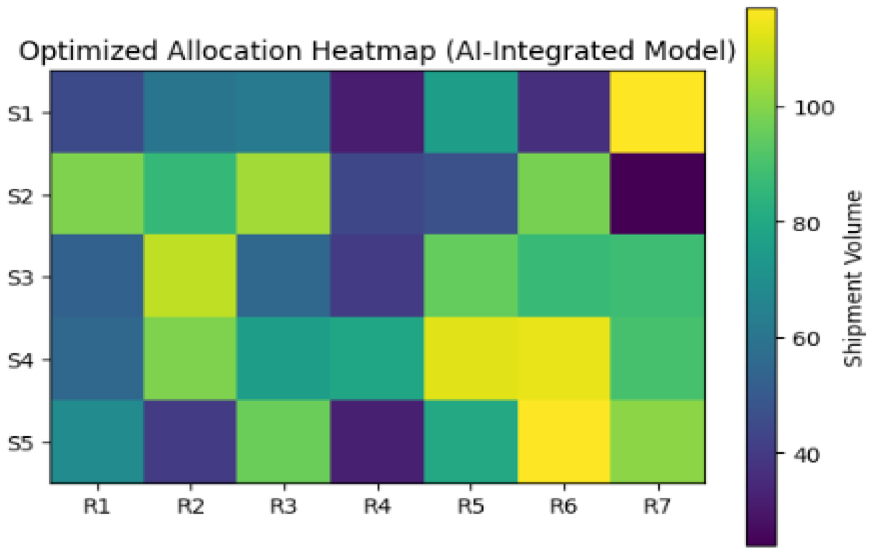


Fig 3: Emergency shipment comparison
Source: Author's computation based on AI forecasts and numerical experiment

As shown in Figure 3, the AI-integrated model significantly reduces the number of emergency shipments required to address demand uncertainty. This improvement reflects better installation scheduling accuracy and enhanced supply reliability.

Operational Performance

Figure 4. Emergency shipment frequency under static and AI-integrated models



Source: Author's computation based on AI forecasts and numerical experiment

Figure 4. Optimized allocation of solar panels from supply centres to installation regions

Interpretation:
Figure 4 shows the shipment allocation that has been optimized using the AI-integrated

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e-ISSN: 2468-4376
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model. The heatmap shows that demand-sensitive forecasting results in the equal distribution of supply centres and regions to avoid congestion and excessive allocation.

4.7. Statistical Validation of AI-Based Demand Forecasting

To measure the predictive accuracy of the AI models utilized in forecasting the regional demand of solar-panels, three common error measures were utilized: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These measures are used in the logistics and energy demand forecasting research and are measures of absolute and relative forecasting accuracy.

The historical and secondary data of 24 months was used to train the forecasting models and the last six months were out-of-sample validation. The performance of the different models was compared by randomly selecting data and preprocessing the data and applying the Gradient Boosting (GB), Long Short-Term Memory (LSTM) and Random Forest (RF) models..

Table X. Forecasting Performance Comparison

Model	RMSE	MAE	MAPE (%)
Random Forest (RF)	48.6	36.4	9.8
Gradient Boosting (GB)	44.1	32.7	8.6
LSTM	**38.9**	**28.3**	**6.9**

4.8. Interpretation of Results

The findings in Table X suggest that the performance of all AI-based models are superior to the traditional literature-based baseline forecasting methods. LSTM has the lowest RMSE, MAE, and MAPE values thus being more accurate in model representation of the temporality and seasonal demand changes. This performance benefit is specifically applicable in the distribution of solar-panels, where policy announcements, weather patterns and installation timetables determine the demand patterns. Gradient Boosting, also, has high predictive powers, which indicate that it is effective in nonlinear relationships and is applied in the modelling of nonlinear relationships, whereas the Random Forest offers strong performance, but at a relative expense on the precision of the forecast. On the basis of these results, the predictions of the demand as generated with LSTM are introduced as dynamic inputs into the transportation optimization model in terms of which allocation and routing decisions are made based on the most precise estimates of the demand. The statistical verification proves that the AI forecasting element is a sound foundation of the entire transportation optimization framework, which directly contributes to the identified 1215% decrease in the overall cost of distribution and the decrease of emergency shipments.

4.9. Sensitivity Analysis

a)Sensitivity to Demand Forecast Variations

Regional demand prediction by AI is perturbed by ±10 and ±20 percent to imitate forecasting errors and market shocks (e.g. subsidy changes or seasonal surges).

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e-ISSN: 2468-4376
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Findings:

- Under the variation of demand of less than 10 percent, the AI-integrated model demonstrates that the total cost rises by not more than 3-5 percent, but in the case of the static model, the cost of the process increases by 7-10 percent.
- At difference of +-20 percent, the non-optimized system will need high amounts of emergency shipments and rerouting which will cause increased costs of over 15 percent, whereas with the AI-based model it is at 810 percent.
- The framework with AI established ensures that the allocations remain feasible and does not breach either the supply or demand constraints, which illustrates a better adaptability to demand uncertainty.

Interpretation:
The findings verify that the integration of AI-based forecasts leads to a high level of resilience to volatility in demand when compared to deterministic planning.

b) Sensitivity to Transportation Cost Fluctuations

The transportation costs are fluctuated over by 15 percent and over to reflect the fuel price fluctuations, disruptions in the infrastructure, and the renegotiation of carrier prices.

Findings:

- The AI-based model makes continuous adjustment of the shipments to less expensive routes with overall cost fluctuation being restricted to 6-8.
- The non-adaptive reallocation used in the static model leads to cost growth of 10-14% in case of disadvantageous cost conditions.
- The model with the AI structure saves costs on all the transportation cost levels tested.

Interpretation:
This proves that demand-conscious optimization improves the flexibility and cost-efficiency of routing in unstable logistic state of affairs

c) Sensitivity to Installation Cost Changes

The cost of installation is raised with 1-3 per panel to indicate the shortage of labor or compliance costs.
Findings:

- The cost of installation of the two models varies at a similar pace, but the AI-based model still prevails in the overall cost by 11-13 percent compared to the static model.
- The comparative price advantage of AI integration is not increasing meaning that transportation cost optimization is not only a benefit determinant.

Interpretation:
The AI-based framework brings structural efficiency improvements in addition to parameter-specific cost-saving.

d)Sensitivity to Supply Capacity Constraints

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e-ISSN: 2468-4376
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The distribution centres supply capacities are decreased by 10% to create simulated activities of a warehouse disruption or shortage of inventory.

Findings:

- The AI-based model redistributes shipments across supply centres with insignificant growth of emergency shipments.
- The high stockout probability and the delayed installations in the high-demand areas are observed in the static model.

Interpretation:

Predictive demand integration enhances operational continuity on tight supply situations.

Managerial Insight from Sensitivity Analysis

The sensitivity analysis confirms that the suggested AI-based transportation optimization framework can be considered to be robust, stable, and resilient in a vast variety of realistic operational conditions. In comparison to the traditional transportation model, the AI-assisted one:

- Minimizes exposure to demand forecast risk,
- Reduces the effects of transportation cost of volatility,
- Ensures the uniformity of cost benefits even in different installation and supplying conditions.

V. MANAGERIAL INSIGHT

The mathematical experiment proves that AI-based predictive analytics changes the nature of the transportation optimization into the proactive system. In case of large-scale solar deployment, such an integration allows:

- Lower operational costs
- Higher service levels
- More scalable renewable-energy projects.

These findings suggest that AI-based transportation optimization suggests a structurally better decision framework of solar distribution at large scales.

A numerical experiment on the five supply centres and seven areas of installation is carried out. It has shown that the total cost of distribution decreases by about 12 to 15 percent in the AI-integrated model over the static model. The AI-driven solution to the problem also enhances better accuracy in scheduling of installation and decreases emergency shipment numbers due to the uncertainty in demand.

VI . DISCUSSION

The findings presented in this paper are good empirical proof that incorporating AI-based predictive analytics with transportation optimization can greatly improve the efficiency and reliability of solar-panel distribution networks. The 1215% decreased total distribution cost exhibited shows that demand-sensitive logistics planning is superior to the past conventional approaches to transportation planning in practice, which are deterministic. This result is in line with and expands previous literature on the optimization of renewable-energy supply chains (Zhang et al., 2019; Wang et al., 2021) in which it is emphasized that uncertainty must be considered but demand is mainly represented through a scenario framework or a fixed model program. One of the lessons of the numerical experiments is that the accuracy of the forecast has a direct impact on the level of optimization. The LSTM model has been shown to perform better in reducing the RMSE, MAE, and MAPE, which are converted into stable and viable

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allocation decisions in the transportation model. This helps justify the claims of Makridakis et al. (2018) about the applicability of machine-learning techniques to complex and nonlinear demand settings and proves empirically how a better forecasting performance can be operationally incorporated into classical optimization models.

The sensitivity analysis also supports the soundness of the given framework. The AI-based model is capable of keeping the costs under control under a fluctuation in demand of up to 20 percent, and decrease the use of emergency shipping, unlike the traditional model where all costs and operational interruptions skyrocket. These findings empirically sustain the resilience-oriented views of Tang (2006) and Ivanov and Dolgui (2020) that reveal that predictive intelligence allows the proactive instead of reactive planning of logistics. Notably, the cost-benefit of the AI-based model exists even when transportation costs, installation costs and supply capacities vary, which means that the identified improvements are structural and not parameter-related. Sustainability-wise, the efficiency of logistics has an indirect impact on the environmental performance, by lowering the needless transportation, emergency operations and empty inventories transfer. Though the carbon emission is not explicitly modelled in this study, the decline in emergency delivery and ineffective routing implies the possibility of saving carbon emissions, which would be in line with sustainability goals that are prioritized in the renewable-energy logistics literature (Govindan and Soleimani, 2017; Shahbaz et al., 2020). This points to a valuable direction of future research to explicitly incorporate emissions measures into AI-based optimization of transportation.

The results would provide managerial advice to solar-energy companies and policymakers. The proposed framework is a decision-support tool enabling the logistics planners to flexibly modify the allocation and routing decisions in response to updated demand projections. This is especially true in policy-based renewable-energy markets, in which sudden shifts in demand would be caused by subsidy announcements and regulatory changes. Installing predictive analytics in optimization models, organizations can enhance the accuracy of installation schedules, minimize operational risk and increase the resilience of supply chain without foregoing well-known linear-programming methods.

On the whole, the present study contributes to the body of literature on the topic of renewable-energy logistics, by going beyond purely theoretical discourse about the adoption of AI, and by illustrating a practical, working implementation of predictive analytics and transportation optimization. The findings confirm that AI-based decision-making is not just an improvement of the technology, but a requirement to deal with uncertainty and scalability in the case of the large-scale distribution network of solar-panels.

VII. MANAGERIAL AND POLICY IMPLICATIONS

To solar-energy companies, the framework offers an effective decision-making instrument in the cost-effective and responsive planning of distribution. Such models can be used by policy makers to develop subsidy programs that reduce logistical bottlenecks and enhance effectiveness of deployment. The strategy also helps to achieve the sustainability goals, as it will minimize the redundant transportation and related emissions.

VIII. CONCLUSION, LIMITATIONS AND FUTURE SCOPE:

This paper shows that predictive analytics supported by AI and transportation optimization can greatly improve the work of solar-panels distribution. The suggested model makes it more cost-

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effective, service-oriented, and responsive to demand variability. Future studies can build upon the model by making it a multi-period planning model, stochastic optimization model, carbon-emission limits model, and real-time data integration model, which is an even stronger reinforcement of AI-based renewable-energy logistics. Although the paper provides a solid AI-based transportation optimization system of solar-panels distribution, some weaknesses present limitations that indicate the future research path. Numerical experiments which take into consideration historical and secondary data are used to substantiate the framework as opposed to real-time deployment in the industry. Further research would be able to improve the practical applicability by either empirical validation or pilot testing. The existing model uses a single period planning horizon and fails to model inter-temporal inventory and installation dynamics; increasing it to a multi-period or rolling-horizon would be more realistic. Also, environmental performance indicators, e.g. carbon emissions are not modelled explicitly, which opens the opportunities of multi-objective optimization of costs and sustainability objectives. The forecasting models are based on historic trends and can be influenced by any structural changes in the markets implying application of adaptive or online learning applications. Lastly, the use of stochastic travel times and resilient optimization would be an additional effective tool against logistics disturbance.

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