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ARTICLE

Predictive Modelling of Dynamic Positioning Vessel Capacity on Offshore Wind Industry

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ABSTRACT

As global efforts to combat climate change intensify, offshore wind farms have emerged as scalable and sustainable solutions. However, their deployment depends heavily on the availability of specialized vessels with Dynamic Positioning (DP) systems such as Wind Turbine Installation Vessels (WTIVs) and Service Operation Vessels (SOVs). Despite their importance, long-term demand forecasting for such vessels remains underexplored, especially in South Korea. This study presents the dDP-W model, a System Dynamics (SD)-based framework that simulates the evolving demand for DP vessels under varying technological, policy, and environmental conditions. Unlike conventional methods based on historical extrapolation, the model uses feedback-driven causality and scenario-based simulations aligned with South Korea's offshore wind roadmap (2026–2036). Three WTIV demand scenarios—baseline, optimistic, and pessimistic—were constructed based on vessel productivity and weather-related downtime. SOV demand was estimated using cumulative turbine counts and fixed vessel coverage ratios. The simulations indicate that WTIV demand peaks in the early 2030s, requiring 6 to 7 vessels depending on conditions, while SOV demand increases steadily, reaching nearly 70 vessels by 2036. These findings highlight the need for early vessel procurement, infrastructure investment, and workforce preparation. By integrating technical, logistical, and policy factors into a dynamic model, this study provides a practical decision-support tool for stakeholders in shipbuilding and offshore energy. The results offer strategic insights to address potential vessel shortages and ensure alignment with national renewable energy goals.

Keywords: System Dynamics; Fleet Capacity; Dynamic Positioning System; Offshore Wind; Vessel

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1. Introduction

The ongoing climate emergency fueled by the rapid accumulation of greenhouse gas emissions, remains one of the most urgent global challenges. Since the ratification of the Paris Agreement in 2015, the international community has worked toward capping the rise in global average temperature to well below 2°C above pre-industrial levels while striving to stay within the 1.5°C threshold [1]. These goals are vital for averting the most devastating consequences of climate change. Yet, the transition toward a low-carbon energy economy has been slower than anticipated in practice. Renewable energy particularly wind power, stands as a central pillar in this effort offering a scalable and sustainable alternative to fossil fuels. Among its various forms, offshore wind farm has emerged as a leading candidate due to its greater generation potential and fewer land-use constraints compared to onshore wind.

Offshore wind farms are capable of generating stable electricity outputs by leveraging stronger and more consistent oceanic wind flows. Unlike onshore installations, they tend to encounter less opposition from local communities and allow for the deployment of larger turbine units. However, these advantages are accompanied by considerable technical and logistical challenges. High construction costs, complex installation procedures, and exposure to volatile marine weather conditions remain critical barriers. As of 2021, wind power (6.6%) and solar power (3.6%) collectively exceeded a 10% share of the global total electricity production [2]. Notably, the offshore wind energy potential in South Korea (annual generation equivalent) is estimated at around 119 TWh/year, which accounts for more than 20% of the annual consumption strategy (553 TWh/year in 2021) achievable solely through offshore wind power. The Levelized Cost of Electricity (LCOE) for both offshore and onshore wind power generation has already demonstrated economic competitiveness surpassing that of fossil fuels (The LOCE for offshore wind power generation has declined from approximately 162 USD/MWh in 2010 to around 115 USD/MWh in 2019, reaching a level of competitiveness comparable to fossil fuel generation costs (109 USD/MWh) [3]. Within the context of the 'Energy Mix', it is anticipated that simultaneous and sustainable growth will occur alongside various energy sources. Nonetheless, recent improvements in turbine design, vessel automation, and installation methodologies have helped reduce these obstacles, contributing to global market growth projections that exceed 10% annually. By 2030, global offshore wind capacity is expected to reach 53 GW and could double by 2040 [4].

South Korea has committed to accelerating its deployment through the "Renewable Energy 3020 Implementation Plan" recognizing the potential of offshore wind farm as follow (**Figure 1**) [4]. This policy framework aims to establish 12 GW of offshore wind capacity by 2030 supported by large-scale projects in regions such as Shin-an, Ulsan, Jeju, and Incheon [4]. To meet these targets, the country must not only develop the turbines themselves but also ensure the availability of specialized maritime infrastructure—particularly vessels equipped with Dynamic Positioning (DP) systems. These include Wind Turbine Installation Vessels (WTIVs), which handle the initial setup of turbines, and Service Operation Vessels (SOVs), which are essential for ongoing operation and maintenance activities.

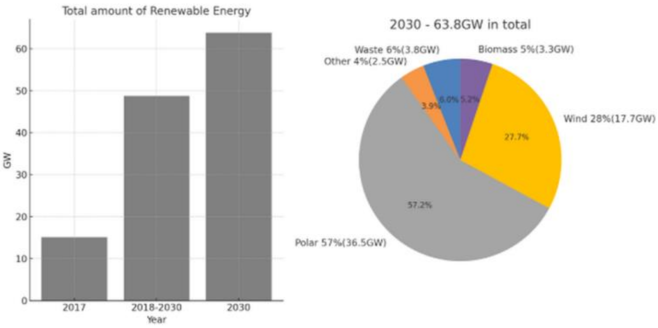

Figure 1. Renewable energy 3020 implementation plan in South Korea.

DP vessels are technologically advanced ships that maintain precise station-keeping capabilities using a combination of thrusters, GPS systems, sensors, and onboard control algorithms. Their automated positioning ability eliminates the need for mooring or anchoring, making them indispensable in the increasingly complex environments of offshore construction. Despite their strategic importance, relatively little research has focused on predicting long-term DP vessel demand—particularly in the context of South Korea's emerging offshore wind market.

While earlier studies have examined various aspects of vessel efficiency, structural optimization, and operational safety [5–9], there remains a lack of robust forecasting tools that can account for the complex evolving interactions between policy targets, environmental factors, and technological development. To address this gap, this study introduces a system dynamics (SD)–based predictive framework referred to as the dDP-W model. Unlike traditional forecasting techniques that rely mainly on historical data trends, the proposed model captures feedback structures and causal relationships among multiple influencing variables. This allows for more adaptive and realistic simulations of future vessel demand, particularly under different installation and policy scenarios.

The novelty of this research lies in its integrated modeling approach. By applying SD methodology—previously used in domains like logistics, urban planning, and aviation—to the forecasting of DP vessel fleet capacity, this study provides a fresh perspective on a critical yet underexplored challenge in the maritime energy sector. Key model parameters include annual offshore wind installation targets, vessel performance characteristics, maintenance requirements, and expected operational downtime due to weather disruptions. These parameters are interconnected through feedback loops that reflect the systemic nature of vessel demand evolution.

In addition to developing the model, this paper includes sensitivity analysis and scenario testing to evaluate how changes in policy objectives, vessel technology, or environmental conditions may influence fleet requirements. These results aim to inform decision-making for shipbuilders, port authorities, and renewable energy planners.

This paper is structured as follows. Section 2 offers a critical review of existing literature related to vessel capacity planning, dynamic positioning technologies, and offshore logistics modeling. Section 3 outlines the technical architecture of DP systems and details the types of vessels currently deployed in offshore wind projects. Section 4 presents the construction and validation of the dDP-W model, including its causal loop diagram and stock-flow structure. Section 5 concludes with key insights, policy implications, and suggestions for future research, including the integration of other vessel types such as cable layers and foundation installation vessels.

2. Literature Review

The deployment of offshore wind farm has seen a surge in academic interest over the past two decades, particularly concerning engineering optimization, installation logistics, and cost-effectiveness. However, while these studies offer valuable insights into technical and operational aspects, they often overlook the systemic implications of offshore wind growth on supporting maritime infrastructure—most notably the availability and capacity of Dynamic Positioning (DP) vessels. As offshore wind projects become larger and more complex, the ability to forecast fleet requirements becomes essential, yet remains underexplored in current literature.

Early contributions to this field have primarily focused on vessel selection and cost control strategies. Walther et al. proposed a multi-criteria decision framework for evaluating installation vessel concepts [5]. Their model considered attributes such as deck space, lifting capacity, transit speed, and dynamic positioning capabilities, all of which impact project efficiency and cost. Similarly, Walker et al. examined installation risk during turbine deployment and suggested improvements in vessel design and operational protocols [6]. These studies highlight the influence of vessel characteristics on offshore wind project performance but stop short of exploring how these vessels' demands might evolve with changing industry conditions.

Kaiser and Snyder developed an economic assessment model for offshore wind projects on the U.S. Outer Continental Shelf [7]. Their approach considered regulatory constraints, sea conditions, and logistical costs. The strength of their analysis lies in its comprehensive scope, yet it primarily serves as a project-level feasibility tool and does not offer long-term fleet capacity forecasting. Meanwhile, Jang and Choi focused on the design evolution and functional specifications of Wind Turbine Installation Vessels (WTIVs), reinforcing the critical role these vessels play in the offshore wind lifecycle [8].

Logistics and operational scheduling also received attention in the work of Kim et al. [9], who introduced simulation-based methodologies to improve transportation and installation efficiency for monopile turbines. Their model accounted for vessel capacity, lifting time, environmental conditions, and transit distances. While effective at optimizing short-term deployment plans, their framework does not address future fleet demands or incorporate macro-level policy factors.

A more recent development is the application of machine learning to predict long-term offshore conditions. For instance, Lee et al. proposed a deep learning-based model to forecast sea and wind conditions, contributing valuable inputs to long-term maintenance and planning efforts. However, the focus remains on environmental forecasting, rather than vessel demand forecasting [10].

In parallel, system dynamics (SD) modeling has become increasingly popular in fields such as transportation, urban planning, and infrastructure development. SD's ability to simulate complex feedback-driven systems makes it well-suited for maritime applications. Jung applied SD to forecast mid-size truck demand by incorporating economic and regulatory variables [11]. Park used SD in the aviation sector to explore airport capacity constraints [12], and Kim analyzed housing market responses to government interventions using feedback-based simulations [13]. These studies demonstrate the flexibility and explanatory power of SD, but its use in maritime logistics, particularly in DP vessel planning, remains limited.

Within the maritime domain, Jo employed SD to analyze how technological advances in autonomous ships might affect workforce demand and training requirements [14]. This study provided an effective precedent for applying SD in maritime workforce planning, but did not consider fleet capacity modeling. Despite growing recognition of SD's potential, no existing research has yet provided a comprehensive, SD-based model for predicting the future demand for DP vessels in offshore wind contexts.

Another noticeable trend in the literature is an overreliance on deterministic models or project-specific simulations. These approaches, while valuable for short-term scheduling or cost estimations, often fail to capture the nonlinear, dynamic nature of the offshore wind market. For example, changes in turbine capacity, evolving regulatory requirements, supply chain disruptions, and climate-related downtime all interact in ways that traditional linear models struggle to account for. The absence of a systemic approach limits the industry's ability to anticipate long-term vessel requirements or make informed infrastructure investments.

Furthermore, a large portion of the existing studies are built on datasets from mature offshore wind markets in Europe or the U.S., which may not reflect the unique geographical, policy, and industrial conditions of emerging markets like South Korea. For instance, South Korea's ambitious offshore wind development plans are tightly linked to national energy transition policies and regional industrial strategies, which introduce specific feedback mechanisms not addressed in most existing models.

Therefore, this study aims to fill a critical gap by introducing a dynamic, feedback-based forecasting tool—the dDP-W model—that simulates DP vessel demand in response to evolving offshore wind capacity targets, vessel performance metrics, and environmental constraints. By adopting a systems-thinking approach and grounding the model in South Korea's policy and industrial context, this work seeks to move beyond descriptive or project-level analyses and provide a strategic, long-term perspective.

In summary, while substantial research has been conducted on offshore wind logistics and vessel optimization, existing studies tend to be narrow in scope, lacking a systemic view of how vessel demand evolves over time. This paper builds upon earlier contributions by integrating macro-level variables into a causal loop framework, enabling the forecasting of future vessel demand under various policy scenarios. The proposed model not only contributes to academic understanding but also offers actionable insights for shipbuilders, policymakers, and energy planners.

3. Dynamic Positioning Systems in Offshore Wind Farm Field

3.1. Dynamic Positioning System

Dynamic Positioning (DP) systems play a central role in enabling offshore wind farm operations particularly in tasks requiring high positional accuracy such as turbine installation, cable laying, and maintenance. A DP system allows a vessel to maintain its position and heading automatically using its own propulsion system without the need for mooring or anchoring. This is especially critical in offshore wind environments where seabed conditions, space constraints, or environmental regulations may restrict the use of conventional anchoring techniques [15].

According to the International Maritime Organization (IMO), a DP system consists of an integrated arrangement of position reference sensors, thrusters, control algorithms, and human-machine interfaces, coordinated by a central DP computer [15]. The DP computer continuously receives input from multiple sources—including satellite-based GPS, laser-based position reference systems, and motion sensors—and translates these data into real-time commands for thruster adjustments. These corrections allow the vessel to remain within an operational envelope despite the influence of wind, wave, and current forces.

The dynamic positioning system consists of main 7 components which are vital to the operation in **Figure 2**.

(1) DP Control Computer – the central processor that calculates position corrections,
(2) Position Reference Systems (PRS) – including GNSS and acoustic systems,
(3) Thruster System – propellers and azimuth drives that control vessel movement,
(4) Power Management System,
(5) Sensor Package – such as gyrocompasses and motion reference units,
(6) Human-Machine Interface (HMI),
(7) Qualified Operators, trained and certified according to Nautical Institute standards [16,17].

The increasing complexity of offshore wind farm environments has led to continuous improvement in DP technology, including redundancy systems (DP2/DP3), dynamic environment modeling, and AI-supported control algorithms. These enhancements ensure safety and efficiency, particularly during installation campaigns that may span weeks at sea and involve precision positioning in dynamic weather conditions [18].

Despite the technical maturity of DP systems, their integration into offshore wind logistics remains a key variable in fleet planning. The ability to maintain safe and stable operations under variable marine conditions determines vessel suitability for installation or maintenance roles. Consequently, any forecasting model for DP vessel demand must consider both the technical specifications of these systems and their performance thresholds in different operational scenarios.

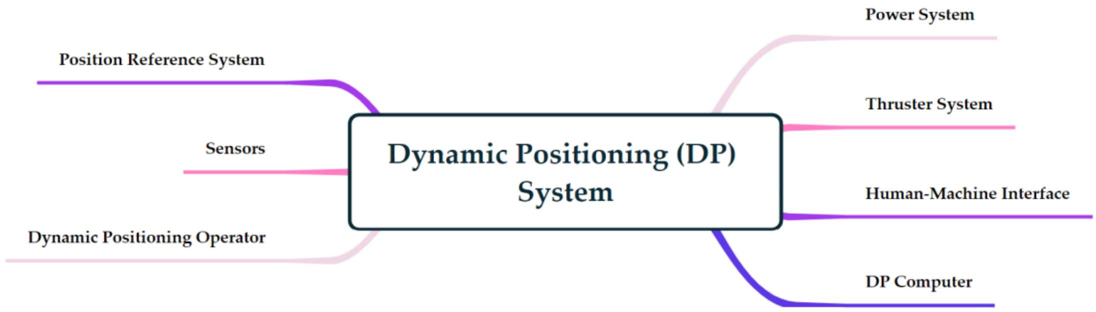

Figure 2. The 7 main components of DP system.

3.2. Vessels Used in the Operation of Offshore Wind Farms

The offshore wind value chain is supported by a range of specialized vessels, each fulfilling a specific function during the project lifecycle. Among these, Wind Turbine Installation Vessels (WTIVs) and Service Operation Vessels (SOVs) represent the most critical DP-enabled assets.

WTIVs are purpose-built or retrofitted ships equipped with heavy-lift cranes, dynamic positioning systems, and jack-up legs in some cases, enabling them to install turbine towers, nacelles, and blades in deep offshore waters. As turbine sizes increase—reaching 12 MW or more—the lifting and stability requirements for WTIVs have also intensified. Modern WTIVs must be capable of transporting and installing multiple large turbines per voyage to maintain economic viability. The cost associated with WTIV operations remains high, particularly due to weather-induced downtime, limited installation windows, and high fuel consumption. Therefore, accurate demand forecasting must incorporate not only the number of turbines but also the technological progression of WTIV capacity and efficiency. Moreover, the average duration for installing a single turbine, along with expected weather-related delays, plays a critical role in estimating the required number of active vessels per year.

Once wind turbines are operational, Service Operation Vessels serve as floating offshore bases for maintenance crews. These vessels are equipped with onboard accommodation, workshops, storage for spare parts, and advanced turbine access systems. Most SOVs operate on DP systems to facilitate precise maneuvering near turbines, allowing for safe technician transfers via gangways or daughter craft. Their deployment cycles typically span several weeks, after which they return to port for restocking and crew rotation. SOVs are distinct from conventional offshore support vessels, such as Platform Supply Vessels (PSVs), due to their enhanced maneuverability, habitability, and operational endurance. While PSVs have been used for installation support in the oil and gas sector, they are generally not well suited for wind farm maintenance due to slower positioning response and limited accommodation capacity. Forecasting demand for SOVs requires a different modeling approach than WTIVs, as their deployment is influenced by turbine maintenance intervals, preventive maintenance schedules (PMS), turbine accessibility during various sea states, and regional weather conditions. As the installed base of offshore wind turbines grows, SOV demand is expected to rise proportionally, though innovations in autonomous inspection or drone maintenance may influence future projections.

4. Predictive Model of Fleet Capacity of DP Vessels

4.1. System Dynamics

System dynamics is a theoretical tool that explores the changes in a system over time to time and seeks to control the system as desired. In this context, a system encompasses a range of fields, including machinery and device systems, nations, organizations, individuals, societies, industries, finance, assets, and economics, among others. System dynamics utilizes both macroscopic system structures and microscopic nodes to regulate the system or to replicate and predict the changes in a phenomenon [19]. In other words, system dynamics is an analysis tool which emphasizes the cyclical causal relationships and feedback structures among problem factors.

Richardson (1995) defined the term "feedback structure" which refers to a causally closed structure formed by interconnected causal relationships among variables [19]. To emphasize feedback structures means identifying the causes of the problem within the internal variables and finding solutions to the problem within the overall structure of the system. In other words, system dynamics seeks to explore solutions to problems within the feedback structure by revealing the underlying causal and effect of the problem. The current situation in the system is always influenced by the past one. The procedure involves problem definition, causal loop diagram, modelling, simulation, analysis, evaluation of model validity, and decision-making processes in **Figure 3** [20].

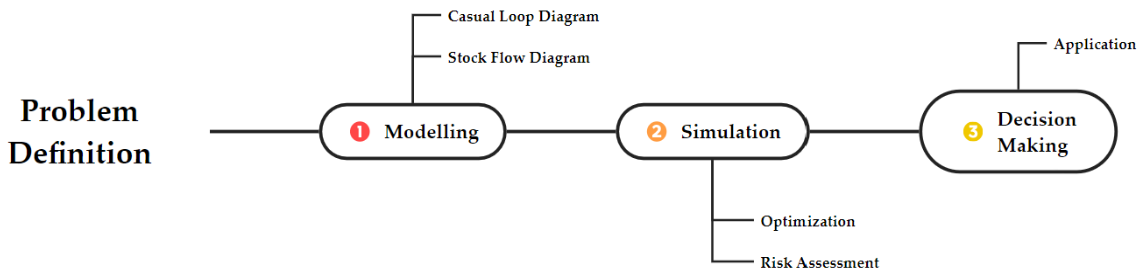

Figure 3. Performance stages in system dynamics.

Causal loop diagram is a qualitative logical model that represents the diagram of relationships between factors when approaching a problem [19]. It involves systematically deconstructing a problem by discovering its underlying variables and interpreting them, and ultimately providing a compelling explanation of the problem's behavior. Therefore, all variables are interconnected through cause-and-effect relationships. Modelling begins with stock-flow diagrams, which consist of stock and auxiliary, illustrating the causal and effect and influences between variables concerning a specific problem. Stocks are variables that change over time, and auxiliaries are variables influenced by certain factors, causing changes that affect the stocks [20].

A feedback system undergoes changes through variables representing its state and effects caused by actions. These two processes do not occur simultaneously and are separated by a time delay over a specific period. This time delay enables the interaction between the two variables, thereby forming a feedback loop. Mathematically, this can be expressed as follows [19].

$$F(x) = \int \frac{F(x_{t+\Delta t}) - F(x_t)}{(t + \Delta t) - t} dt = \int f(x_t) dt \tag{1}$$

$$S : State = F(x)$$

$F(x_{t+\Delta t})$: *State on time of* $(t + \Delta t)$

$f(x_t)$: *amount of state change caused by an Action*

4.2. Casual Loop Diagram

It presents the causal loop diagram designed to examine how the scale and composition of DP vessel operations adapt dynamically in response to the growth of the offshore wind farm industry, which constitutes the primary focus of this paper (**Figure 4**). This predictive model is referred to as the dDP-W model.

As per the "10th Basic Plan of Long-Term Electricity Supply and Demand" in **Figure 5**, unveiled by the Ministry of Trade, Industry, and Energy in January 2023, there are ambitious goals to substantially boost the share of renewable energy generation, particularly wind power, aiming for a 30.6% contribution by 2036, as depicted in **Figure 5** [19,21]. Moreover, while onshore wind power has historically been the primary driver of growth, a significant portion of the wind power expansion outlined in this foundational plan is directed towards offshore wind power projects. The annual installation of offshore wind turbines is determined by the target generation capacity for offshore wind farms, which steadily escalates in accordance with the established plans.

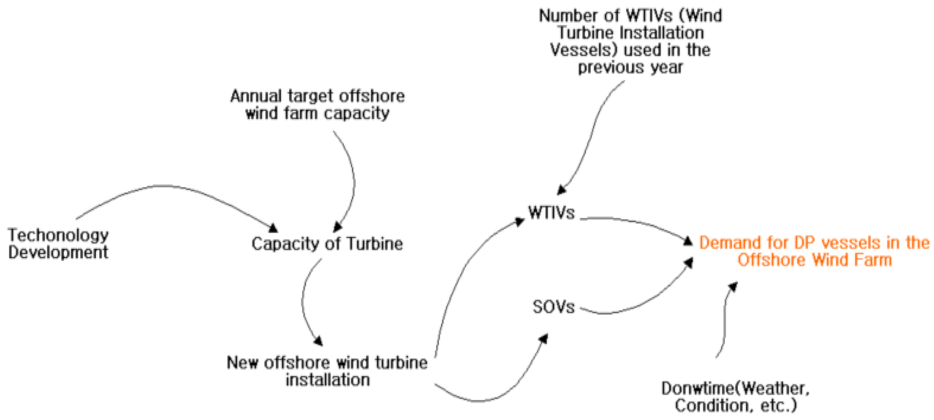

Figure 4. Casual loop diagram of dDP-W model.

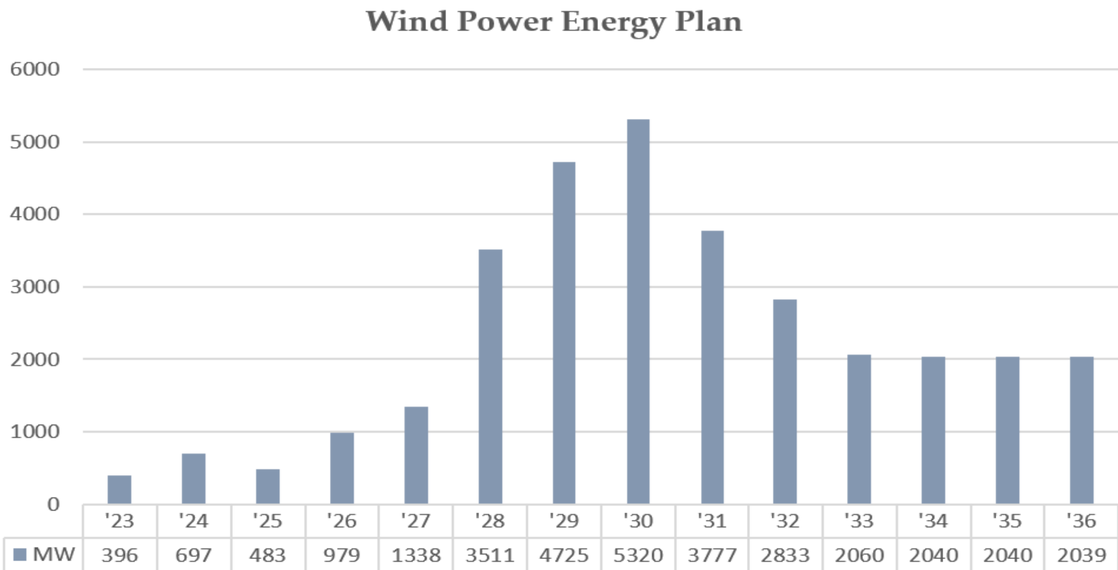

Figure 5. 10th Basic plan of long-term electricity supply and demand.

The DP vessels including WTIVs and SOVs in the offshore wind farm industry can anticipate and plan for service demand. In the initial phases, these vessels (WTIVs and SOVs) address the demand by either commissioning new constructions or utilizing existing operational vessels. The number of WTIVs required is linked to the number employed in the previous year and the annual installation capacity of offshore wind turbines for each WTIV. Furthermore, installed offshore wind turbines undergo routine inspections through a PMS to proactively prevent accidents. To support this maintenance process effectively, SOVs play a crucial role. These SOVs operate within a feed-back system, with their schedules and demand being determined based on the operational status of offshore wind turbines and the prevailing weather conditions suitable for safe operations.

4.3. Stock Flow Diagram

It is depicted as a stock-flow diagram employed to forecast the demand for DP vessels in response to the expansion of the offshore wind farm industry as shown in **Figure 6** [22].

This diagram outlines the anticipated quantity of DP vessels necessary for the construction of offshore wind farms, drawing insights from the energy plan specified earlier, spanning the years 2023 to 2036 [23]. The analysis takes into consideration feedback loops influenced by factors derived from the causal diagram.

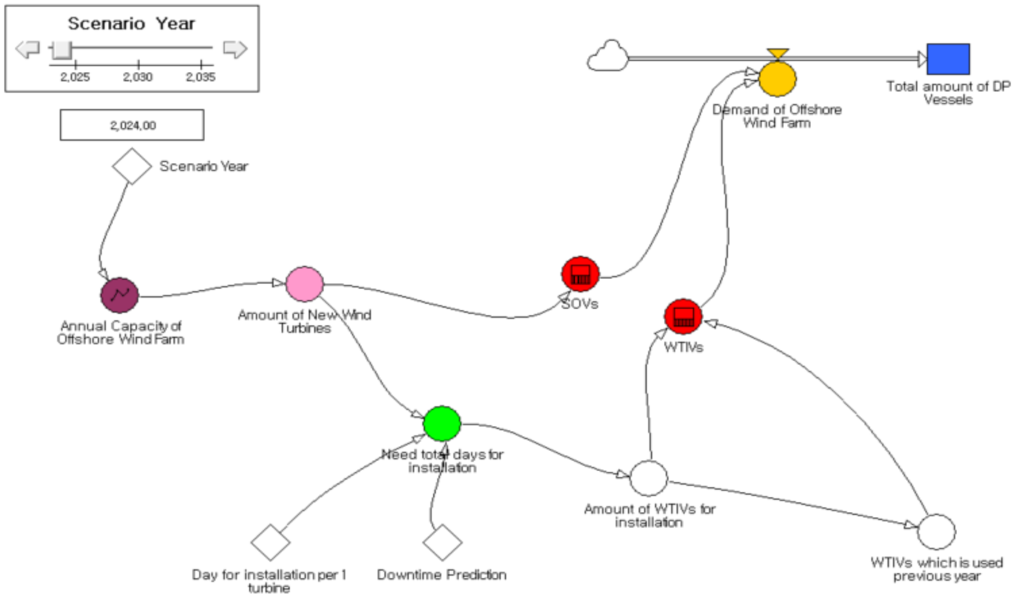

Figure 6. Stock flow diagram of dDP-W model.

In the dDP-W model according to the stock flow diagram, N(DPw)t, WTIV t, and SOV t are defined as the following equations (2) and (3). The N(DPw)t is the demand for DP vessels used in the offshore wind farm until the time t. WTIV t is the demand for WTIV, and SOV t is the demand for SOV until the time t.

$$N(DP_W)_t = \int (WTIV_x + SOV_x)dx \tag{2}$$

$$WTIV_w = \frac{N(WT)_t \cdot D(WT) + Y \cdot D(DT)}{Y} / \frac{Y \cdot \left(1 - D(DT)\right)}{D(WT)} \tag{3}$$

$N(WT)_t$: amount of new offshore wind turnine installation at time t
D(WT): the date of installation per one new offshore wind turbine
D(DT): the expected date of downtime per year
D(PMS): the date of PMS operation per one offshore wind turbine

In the offshore wind farm field, efforts are being made to reduce the cost of electricity generation by increasing the capacity of turbines and scaling up key components such as blades and nacelles. As of 2021, the average turbine capacity in European offshore wind farms was 8.5 MW per turbine, which is more than double the average capacity compared to ten years ago. Due to the significant proportion of the overall system installation and maintenance costs attributed to substructures and submarine cables, it is economically advantageous to construct wind farms with a limited number of large-capacity turbines.

To address periods of downtime, the conventional practice involves allocating approximately 30% of the time to offshore project planning. For the model simulation, the widely used value of 30% has been incorporated. However, the precise information about the specific area and vessel performance should be taken into account for actual planning purposes. Downtime will be primarily influenced by the weather conditions in the offshore wind farm installation area, and the operational envelope limits of the vessels deployed should also be a significant consideration. Additionally, in the future, WTIVs and SOVs are expected to become larger, and the performance of their onboard DP systems and propulsion systems is likely to improve. Therefore, downtime is expected to decrease progressively.

4.4. Scenario Analysis and Model Validation

To evaluate the applicability and predictive strength of the proposed dDP-W model, a comprehensive scenario-based simulation was conducted using South Korea's national offshore wind farm installation roadmap spanning from 2026 to 2036. This analysis aimed to quantify the yearly demand for Wind Turbine Installation Vessels (WTIVs) and Service Operation Vessels (SOVs) under varying technological, environmental, and policy-related conditions, thereby assessing the model's responsiveness to key variables influencing fleet planning.

4.4.1. Scenario Design

Three forecasting scenarios were developed to reflect different operating assumptions concerning vessel efficiency, installation productivity, and meteorological conditions (**Table 1**).

Table 1. Scenario details.

Baseline Scenario (Scenario A)	Assumes a WTIV can install 100 turbines annually, with each turbine rated at 10 MW, yielding a total annual installation capacity of 1,000 MW per vessel. This scenario reflects average operating conditions with 30% weather-induced downtime.
Optimistic Scenario (Scenario B)	Reflects improved vessel operability and weather forecasting systems, enabling a WTIV to install 120 turbines per year (1,200 MW), with reduced downtime at 20%.
Pessimistic Scenario (Scenario C)	Incorporates adverse weather and logistical inefficiencies, resulting in a reduced WTIV capacity of 80 turbines per year (800 MW), and extended downtime of 40%.

For SOVs, demand was estimated based on the cumulative number of operational wind turbines rather than installation targets. Each SOV was assumed to support maintenance activities for approximately 45 turbines annually, taking into account routine preventive maintenance schedules, accessibility windows, and offshore weather variability.

4.4.2. Forecasted WTIV Demand

Table 2 summarizes WTIV demand projections under the three scenarios, calculated by dividing annual installation targets by vessel-specific productivity rates:

Table 2. WTIV Demand.

Year	Installation Target (MW)	Scenario 1 WTIVs	Scenario 2 WTIVs	Scenario 3 WTIVs
2026	979	1	1	2
2027	1,338	2	2	2
2028	3,511	4	3	5
2029	4,725	5	4	6
2030	5,320	6	5	7
2031	3,777	4	4	5
2032	2,833	3	3	4
2033	2,060	3	2	3
2034	2,040	3	2	3
2035	2,040	3	2	3
2036	2,039	3	2	3

4.4.3. Forecasted SOV Demand

SOV demand was computed based on the cumulative number of installed turbines, assuming each SOV can service approximately 45 turbines per year (**Table 3**).

Table 3. SOV demand.

Year	Cumulative Capacity (MW)	Cumulative Turbine (10 MW/Unit)	SOVs
2026	979	98	2
2027	2,317	232	5
2028	5,828	583	13
2029	10,553	1,056	23
2030	15,873	1,588	35
2031	19,650	1,965	44
2032	22,483	2,249	50
2033	24,543	2,455	55
2034	26,583	2,659	59
2035	28,633	2,864	64
2036	30,672	3,068	68

4.4.4. Strategic Implication

Demand for WTIVs peaks between 2028 and 2030, reaching as many as 6 vessels in the baseline scenario and up to 7 in the pessimistic case. These findings highlight the urgency of advanced procurement and shipyard capacity planning. Due to the cumulative nature of turbine maintenance, SOV demand escalates steadily over time, requiring totally 68 vessels by 2036. This indicates a need for parallel investments in crew training, port infrastructure, and maintenance logistics. Meteorological downtime significantly affects vessel requirements. Reducing downtime through enhanced forecasting and vessel reliability can decrease required fleet size by 15–25%. WTIV construction lead times (typically 2–3 years) necessitate proactive forecasting. The dDP-W model offers a quantifiable framework for aligning vessel procurement with national energy transition goals. In summary, the scenario simulation demonstrates the dDP-W model's utility as a decision-support tool, capable of quantifying infrastructure demand under variable conditions. The model's output provides actionable insights for stakeholders involved in vessel construction, port logistics, offshore wind project planning, and maritime workforce development.

5. Conclusion

This study addressed a pressing challenge within the offshore wind farm sector: the accurate prediction of fleet capacity requirements for Dynamic Positioning (DP) vessels, which are critical enablers of wind turbine installation and maintenance in marine environments. In response to the rapidly expanding offshore wind market, particularly in South Korea, a system dynamics-based model—referred to as the dDP-W model—was developed and validated to forecast the demand for both Wind Turbine Installation Vessels (WTIVs) and Service Operation Vessels (SOVs) from 2026 to 2036.

The conclusion presented here reflects revisions made in alignment with reviewer feedback, including improved scenario modeling, the incorporation of realistic vessel productivity data, and the integration of cumulative turbine-based SOV demand. These enhancements have strengthened the model's realism and broadened its applicability to diverse stakeholder groups, such as shipbuilders, energy policymakers, and port authorities.

By simulating multiple policy and weather-related scenarios, the dDP-W model has demonstrated its utility in revealing how vessel demand varies with fluctuations in offshore wind installation targets, technological progress, and environmental conditions. Results indicate that while WTIV demand is strongly tied to annual installation volume and weather-related downtime, SOV demand is largely driven by the accumulated number of operational turbines, growing steadily over time and necessitating parallel investments in maintenance infrastructure and workforce capacity.

Furthermore, the model illustrates the strategic importance of early planning. Given the two- to three-year lead time required for WTIV construction, accurate forecasts such as those provided by the dDP-W model are essential for mitigating risks of capacity shortages and optimizing long-term investment planning. These insights can contribute significantly to the success of national renewable energy transition efforts.

Although the model incorporates robust structural logic and scenario testing, it is subject to limitations. For example, the assumption of a full transition to 10 MW-class turbines simplifies a more complex reality involving phased technological adoption. Similarly, SOV demand was projected using fixed service coverage estimates without accounting for potential advances in autonomous maintenance solutions or drone-based inspections. Future research should aim to incorporate a broader set of vessel types—including cable layers, foundation installation vessels, and ROV support units—into the model framework.

Additionally, integrating high-resolution weather models and data-driven turbine failure rates could improve predictive accuracy. Despite these limitations, the dDP-W model represents a meaningful step toward a dynamic, systems-based understanding of DP vessel demand within the offshore wind ecosystem. Ultimately, this research underscores the importance of using feedback-driven modeling to inform the scaling of maritime infrastructure in parallel with offshore renewable energy goals. As South Korea and other nations intensify efforts to meet carbon neutrality targets, tools such as the dDP-W model can support more resilient, data-informed planning across the maritime energy supply chain.

Author Contributions

Conceptualization, J.K. and H.P.; methodology, J.K.; software, J.K.; validation, J.K. and H.P.; formal analysis, J.K.; investigation, J.K.; resources, J.K.; data curation, J.K.; writing—original draft preparation, J.K.; writing—review and editing, H.P.; visualization, J.K.; supervision, H.P.; project administration, H.P. All authors have read and agreed to the published version of the manuscript.

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Not applicable.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Conflicts of Interest

The authors declare no conflict of interest.

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