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Developing a Markov Decision Process Model to Support ESG Decision-Making in the International Construction Market

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Abstract

International contractors face complex decision-making challenges under uncertain and rapidly changing institutional environments. This study addresses these challenges by proposing a Markov decision process (MDP) model to optimize Environmental, Social, and Governance (ESG) strategies. The proposed model consists of four key components: state, action, transfer probability, and reward function. Data collected through structured surveys on institutional pressures, ESG actions, and anticipated future pressures were used to measure the state, action, and transfer probability, respectively. ESG performance metrics, along with the associated costs and benefits for construction companies, were gathered to train a neural network model for representing the reward function. The value iteration method was used to derive optimal ESG decision-making strategies in the international construction market. The findings reveal that the MDP framework effectively identifies optimal ESG actions for contractors, providing practical insights to maximize rewards and adapt to dynamic institutional conditions. This approach supports contractors in achieving their operational and strategic goals in international markets.

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[‡] Revised the paper

1 Introduction

In recent years, the global landscape has been marked by increasing uncertainty and rapid changes (Worley & Jules, 2020), which posed significant challenges for businesses operating in volatile environments. International contractors, in particular, face heightened pressures due to the complex and dynamic nature of the international construction market, which involves large-scale investments, lengthy project timelines, and a variety of institutional environments (Jung et al., 2012). Operating across borders, these contractors are faced with evolving institutional pressures, making adaptability and resilience essential to project success (Hult et al., 2020; McCarthy et al., 2010). Unlike static environments, cross-border settings require international contractors to continuously respond to changing institutional demands, from local regulatory adjustments to shifting societal expectations. As these pressures evolve, they necessitate flexible and responsive management strategies that ensure both compliance and operational efficiency.

To address these complexities, international contractors are increasingly adopting Environmental, Social, and Governance (ESG) strategies as part of their broader approach to managing institutional pressures. ESG strategies not only help firms align with regulatory requirements and societal expectations but also enhance their legitimacy and long-term sustainability (Ramanujam, 2009). Legitimacy theory posits that organizations seek approval from society by demonstrating behaviors that align with socially constructed norms and values (Suchman & M., 1995). In the context of ESG, legitimacy implies that firms can enhance their corporate reputation and stakeholder trust by proactively addressing environmental and social concerns (Ye et al., 2022). Moreover, in highly regulated or publicly scrutinized sectors, ESG practices serve as a vital means of securing legitimacy and managing reputational risks, particularly in turbulent environments (Campbell, 2007; Wang et al., 2019).

However, managing ESG in a dynamic and uncertain institutional environment adds considerable complexity to the decision-making process. Institutional pressures are multifaceted, with both external and internal dimensions influencing firms' strategies. Traditional classifications describe institutional pressures as coercive, normative, and mimetic. Coercive pressures arise from formal regulations and compliance demands, normative pressures reflect societal values and professional standards, while mimetic pressures stem from the tendency of firms to imitate successful peers in uncertain environments(DiMaggio & Powell, 1983). Building on this, Borini et al. (2018) differentiate between external institutional pressures—such as the host country's regulatory and cultural demands—and internal ones, which stem from corporate culture and strategic objectives. This dual-layered pressure landscape further complicates the decision-making process for international contractors, therefore understanding how to navigate these pressures has become a crucial element of project management in cross-border settings (Ho et al., 2023).

This complex landscape has led to a growing recognition that traditional decision-making frameworks often fall short in addressing the uncertainties international contractors face. While current literature provides foundational insights into ESG decision-making (Brigham et al., 2023; Molin et al., 2023), it often focuses on general guidelines or reactive approaches to institutional pressures, offering limited support for proactive ESG decision-making in today's increasingly uncertain environment for international contractors. To address this need, this study introduces a Markov Decision Process (MDP) framework as a tool for ESG decision-making in uncertain institutional contexts. Widely applied in sequential decision-making under uncertainty, the MDP model is particularly suited to complex environments, enabling firms to evaluate a range of potential actions and their consequences across different contexts (Alagoz et al., 2010; He & Jiang, 2018). By incorporating probabilities of state transitions and reward functions, the MDP approach provides a structured, adaptive model that supports continuous ESG strategy adjustments.

The purpose of this study is twofold: first, to develop a decision-making model that identifies the optimal ESG strategies for international contractors navigating periods of volatility; and second, to clarify the specific conditions under which certain actions maximize ESG outcomes amid varying institutional pressures. By introducing a proactive, adaptive ESG decision-making framework, this research moves beyond traditional reactive approaches, addressing critical gaps in the literature and offering actionable insights to guide contractors in complex, dynamic global environments.

2 The Proposed MDP Model

2.1 Model Assumptions

There are three assumptions for the proposed MDP model shown as follows:

(1) Assumption 1: Markov property in ESG decision-making. According to the Markov property, a foundational principle of the MDP framework, it is assumed that the transition from one state of institutional pressure to another depends solely on the current state and the chosen ESG action, rather than the sequence of previous states. This assumption implies that the future state of institutional pressures faced by an international contractor is determined only by the current level of pressures and the ESG strategy implemented at that moment. This simplifies the decision-making process, enabling the use of MDP to model and optimize the contractor's ESG strategy in a dynamic environment.

(2) Assumption 2: The implementation of ESG practices by international contractors under varying institutional pressures is a decision problem. Confronted with diverse and complex institutional environments, contractors must determine how to implement ESG. It can be thus assumed that ESG implementation is a decision problem in which contractors select their response strategy. This assumption frames ESG implementation as an action, with the key focus on identifying the "best" course of action. In essence, contractors assess the potential outcomes of their decisions to guide their actions.

(3) Assumption 3: Observability of the external environment. The external environment is assumed to be fully observable to international contractors. This means the contractors' perception of the institutional environment aligns precisely with the actual external conditions, allowing for clear decision-making based on the current state information. Consequently, decisions can be made based on the known and observable state of the environment without requiring estimation or inference about hidden variables. This full observability simplifies the modeling process, enabling direct optimization of ESG strategies within the model.

2.2 Model Components

The MDP is a mathematical model for decision-making in uncertain environments, consisting of four components, State (S), Action (A), Transfer Probability (P), and Reward Function (R). The set of states is all possible situations faced by the decision maker, the set of actions is all possible actions that the decision maker can take in each state, the transfer probability is the probability of transferring to the next state after each action is taken in each state, and the reward function is the instantaneous reward obtained after each action is taken in each state. MDP can be solved for the optimal strategy, i.e., what action can be taken to maximize the desired reward in each state.

State **(*S*)** represents the level of internal (e.g., from employees and parent companies) and external (e.g., from competitors and society) institutional pressures faced by an international contractor. By capturing these current pressure levels, we ensure that the state contains all the necessary information for predicting future outcomes and guiding decisions, without the need to consider past states, which aligns with the Markov property.

To quantify these states, we map internal and external pressures onto a two-dimensional coordinate system, with internal pressures (IIP) on the X-axis and external pressures (EIP) on the Y-axis, where each coordinate represents the intensity of pressures faced by contractors. Then, the international contractors' state set, $S = \{s_1, s_2, \cdots, s_9\}$, defines nine unique combinations of institutional pressure levels, categorizing the contractor's environment into distinct states.

Action ($\boldsymbol{A}$) in this model represents the strategies an international contractor might use to address ESG responsibilities across various states. Actions are organized into three dimensions: Environmental (E), Social (S), and Governance (G), capturing a broad range of potential ESG behaviors.

To measure these actions, each ESG dimension is further divided into levels of intensity, from low to high, resulting in 27 unique actions, each representing a specific combination of ESG strategy intensities. This action set, denoted as $A = \{a_1, a_2, \cdots, a_{27}\}$, enables analysis of how contractors adjust their ESG strategies in response to different institutional pressures.

Transfer Probability ($\boldsymbol{P}$) in this model represents the likelihood that an international contractor will transition between states of institutional pressure after implementing a specific ESG action, capturing the uncertainty and dynamic nature of the environment. This model assumes transitions depend only on the current state and chosen action, in line with the Markov property.

To estimate these probabilities, we conducted a survey among international contractors to collect data on their current state, implemented ESG actions, and anticipated state transitions. Using the Law of Large Numbers, we approximated transition probabilities by calculating the frequency of state changes. Specifically, $p_{ij}(a_k)$, the probability of moving from state s_i to s_j after action a_k, is determined by the ratio of respondents who transitioned from s_i to s_j following a_k to the total respondents who took a_k while in s_i.

Reward Function ($\boldsymbol{R}$) assigns a value to each state-action pair, indicating the desirability of a particular action in a given state for an international contractor. This MDP model captures how decisions in response to current pressures influence future outcomes, making it suitable for optimizing ESG strategies in dynamic and uncertain environments.

To quantify R, we first calculate the Cost-Benefit Ratio (CBR) as shown in formula (1), for a sample of construction-related companies and combine these values with their ESG scores across Environmental, Social, and Governance dimensions. These combined CBR and ESG scores serve as input data to train a neural network model, establishing a predictive relationship between ESG scores and the reward R (i.e., the CBR).

$$CBR = \frac{Benefit}{\mathrm{Cos}t} \tag{1}$$

Once the CBR values are calculated, the next step involved processing this data and training the neural network model to establish a predictive relationship between the ESG scores and the reward R. The ESG scores for various companies, spanning the Environmental, Social, and Governance dimensions, were used as input variables (x_1, x_2, x_3) in the neural network model. The output variable (y) represented the reward R, which is quantified by the CBR. As indicated in formula (2), $f(\cdot)$ denotes the function learned by the neural network. Once trained and validated, the model is applied to predict the reward R for international contractors using ESG scores collected from survey responses. By feeding the survey-derived ESG scores into the model, the corresponding reward R values are generated, providing an estimate of the expected rewards that each contractor could achieve by implementing specific ESG strategies under varying institutional pressures.

$$y = f(x_1, x_2, x_3) \tag{2}$$

2.3 MDP Model Optimization and Policy Derivation

To evaluate the optimal decision-making process for international contractors concerning ESG, we implemented a MDP using value iteration. The value iteration algorithm was employed to calculate the optimal value function $V^*(s)$. This method iteratively updates the value of each state based on the Bellman optimality equation (referenced as formula (3)), where γ is the discount factor, s represents the current state, a is the action taken, and s' denotes the next state, and l, representing the number of pressure states, is 9. The process continues until the change in the value function, δ, is less than a small threshold, indicating convergence. In this study, γ was set to 0. This choice reflects the immediate nature of decision-making in a rapidly changing environment, where future rewards are considered less relevant, thereby placing emphasis on current outcomes. This assumption is aligned with the reality faced by international contractors operating in volatile markets where long-term planning is overshadowed by immediate pressures and uncertainties.

$$V^*(s) = \max_{a \in A} \sum_{i=1}^{l} P(s' | s, a)[(R(s, a, s') + \gamma V^*(s)] \quad (3)$$

After achieving convergence in the value iteration process, the optimal policy π^* was determined. The policy dictates the best action a to take in each state s, maximizing the expected reward. The policy was derived by selecting the action that maximizes the value function:

$$\pi^* = \arg\max \sum_{i=1}^{l} P(s' | s, a)[(R(s, a, s') + \gamma V^*(s)] \quad (4)$$

The results of the value iteration algorithm yielded the optimal value function V^* and the corresponding optimal policy π^* for each state.

3 Data Analysis, Findings and Discussions

3.1 Data Collection

To support the calculation and derivation of the MDP components, especially for the transfer probability P and the reward function R as outlined in the previous stages, a comprehensive data collection process was undertaken.

3.1.1 Collection of S, A, and P for International Contractors

Specifically, for the determination of the state S, action A and transfer probability P, the data was gathered through a survey targeting international contractors. The snowball method was employed to conduct the questionnaire survey from December 2023 to January 2024. A total of 235 questionnaires were distributed, with 162 responses received, yielding a response rate of 68.94%. Of these, 125 questionnaires were fully completed, resulting in an effective response rate of 77.16%. The survey was designed to be anonymous, and participation was voluntary.

3.1.2 Collection of CBR for Model Training Outputs (Y)

Indicator type	Indicators
Cost	Environmental protection tax
	Energy consumption
	Charitable input
	Audit fee
	Innovation research and development expenses
Benefit	Environmental honors or awards
	Whether passed ISO9001 and ISO14001 certification
	Employee satisfaction
	Corporate reputation
	Innovation achievement
	Governance achievement

Table 1: Cost-benefit indicators

Data needed for calculating the reward function R was gathered from various sources, with the CBR serving as the key metric. Cost indicators were sourced from CSR reports and the CSMAR database, covering items such as environmental protection taxes, energy consumption, charitable contributions, audit fees, and R&D expenses, all converted into monetary values to assess ESG costs clearly. Benefit indicators were measured using non-financial metrics such as environmental honors, certifications (e.g., ISO9001, ISO14001), employee satisfaction, corporate reputation, innovation achievements, and governance outcomes, as detailed in Table 1. This approach provides a comprehensive CBR by balancing financial costs against qualitative benefits, enabling an effective evaluation of ESG strategies. The CBR then serves as the dependent variable in this analysis, offering a balanced assessment of ESG strategy success.

3.1.3 Collection of ESG Data for Model Training Inputs (X)

To enhance the predictive modeling described in section 2.2, the dataset was further refined with comprehensive ESG scores from the Bloomberg database for various companies, which provided comprehensive ESG scores for various companies. This dataset was crucial for establishing the relationship between a company's ESG performance and the corresponding reward R. To ensure the relevance and accuracy of the analysis, a rigorous data screening process was applied. This process involved excluding financial firms, such as those in the banking, securities, and insurance sectors, due to their unique characteristics that could skew the analysis. Additionally, companies with special listing statuses (e.g., ST or *ST) were removed. The final dataset, focused on companies related to the construction industry, consisted of 60 listed firms in China for the year 2022. This dataset was then used to train a neural network model designed to predict the international contractors' reward R based on the collected ESG scores.

3.2 Data analysis and results of the components

3.2.1 Visualization and Analysis of S, A, and P for International Contractors

Using data from 125 completed questionnaires, we analyzed the relationships between states (S), actions (A), and transfer probabilities (P) for international contractors. Figure 1 provides a bubble plot illustrating the frequency and distribution of actions across nine institutional pressure states. The size of each bubble represents the relative frequency of a specific action within a particular state, while the color intensity indicates the magnitude of the corresponding values.

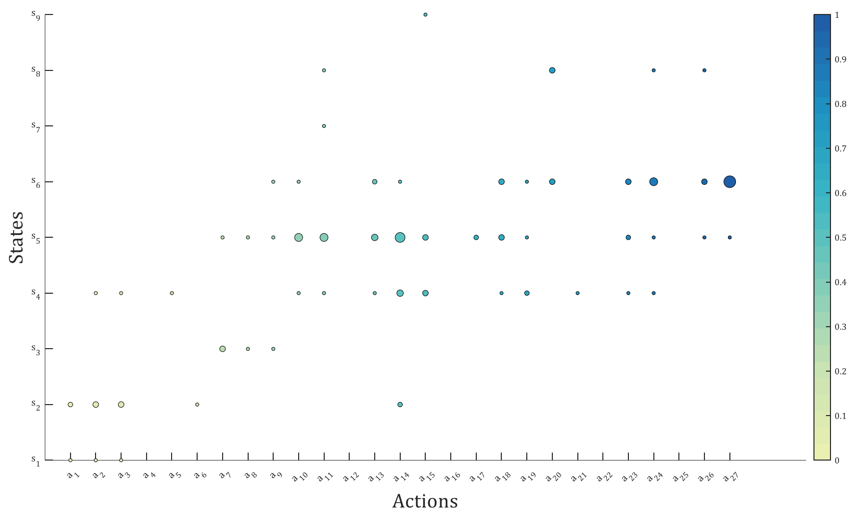

Figure 1: Distribution of ESG actions across institutional pressure states

Figure 1 reveals distinct patterns in the adoption of ESG strategies across different institutional states. For lower-pressure states (e.g., $s_1$and s_2), fewer and less intensive actions are typically implemented, as evidenced by smaller and lighter-colored bubbles concentrated in the left portion of the action axis. This suggests a cautious approach to ESG implementation when institutional pressures are minimal. In contrast, states under medium to high institutional pressures (e.g., s_5 and s_6) exhibit larger bubbles across a broader range of actions, highlighting increased adoption and intensity of ESG strategies in response to elevated pressures. For instance, state s6 demonstrates the most diverse action distribution, with actions a_{23}, a_{24}, and a_{27} showing particularly high frequencies.

Following this, the transfer probabilities were recalculated to better visualize the dynamics of state transitions in response to specific ESG actions. The updated state transition network is depicted in Figure 2, where the red nodes represent the nine institutional pressure states (s1 through s9), and the blue arrows indicate all possible transitions between these states based on the contractors' actions. The probability of each transition is labeled on the arrows alongside the corresponding ESG actions. The results showed that while ESG actions are necessary for managing institutional pressures, their effectiveness is closely tied to both the starting pressure state and the intensity of the actions taken. (1) Contractors in lower-pressure states may experience an increase in pressure if they implement low intensity ESG actions. For example, contractors in s_2, despite being in a relatively low-pressure state, transitioned to higher-pressure states like s_9 after adopting weaker actions such as a_2, indicating that insufficient ESG engagement in these contexts can lead to heightened external pressures. This suggests that contractors in low pressure environments face the risk of pressure escalation if they do not take robust actions to meet external expectations. (2) In high-pressure states, such as s_9, the analysis reveals a distinct trend: even when contractors adopt relatively strong ESG actions, there is often little movement towards lower pressure states. For instance, contractors in s_9 who implemented higher-intensity actions like a_{15} frequently slightly transitioned to s_6.

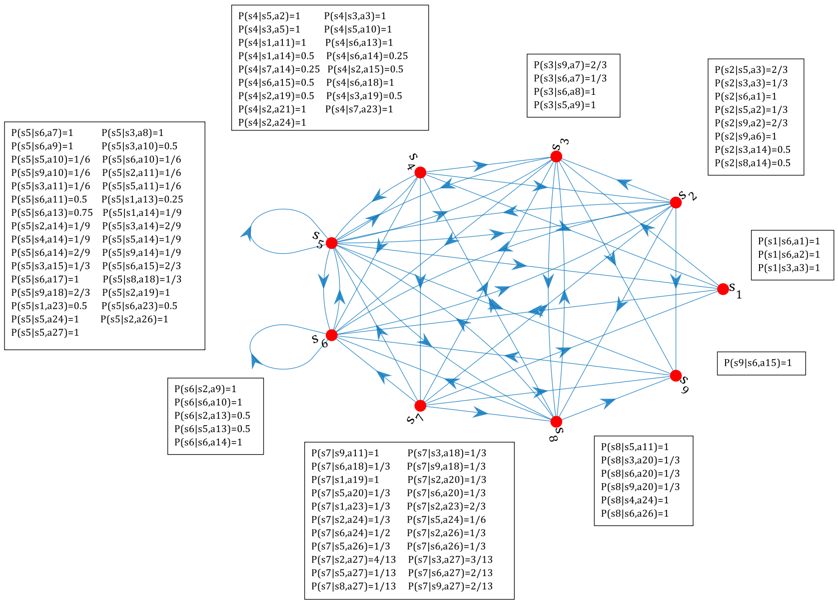

Figure 2: Transition visualization for international contractors' states

3.2.2 Neural Network Modeling for Reward Function Prediction

After calculating the transfer probabilities, the next step was to process and analyze the reward function R, modeled using a neural network. The input data consisted of x (ESG scores) and y (CBR values), which were used to train the network. As shown in Figure 3, the neural network architecture includes an input layer, a hidden layer, and an output layer. The input layer accepts three values corresponding to the ESG dimensions. These inputs are passed to the hidden layer, which contains 10 neurons. Each neuron in the hidden layer computes a weighted sum of the inputs using a weight matrix W and a bias b. The resulting output is passed through an activation function (represented by the curved symbol) to introduce non-linearity, allowing the network to learn more complex patterns. The weight matrix W in the hidden layer has dimensions of 3×10, corresponding to the three inputs and ten neurons. After the hidden layer processes the data, the output is passed to the final output layer, which consists of a single neuron. The output layer applies its own weight matrix and bias before generating the final prediction.

The neural network was trained using the Levenberg-Marquardt backpropagation algorithm. During training, the weights and biases were adjusted to minimize the error between the predicted and actual CBR values, optimizing the model's accuracy. This neural network structure was specifically designed to capture the relationship between ESG scores and CBR values.

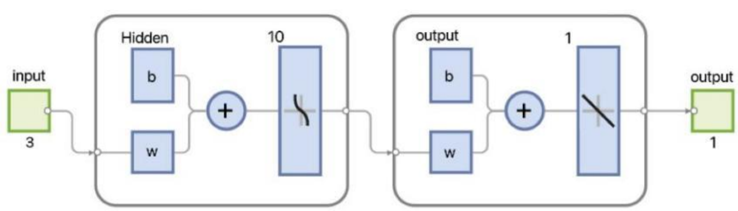

Figure 3: Two-layer feedforward network

3.2.3 Model Validation and Performance Evaluation

To ensure robust results, the data set is split into three train, validation, and test data sets with a ratio of [14:3:3]. Thus, the algorithm is trained in randomly chosen data from 42 companies. Then, the model is validated in the remaining randomly chosen 9 companies' data and tested in the remaining 9 companies' data. The results depicted in Figure 4 strongly validate the effectiveness of this neural network model across various datasets. The model achieved a commendable correlation coefficient R of 0.765 on the training set, reflecting a robust alignment between the predicted and actual data. In this context, an R value above 0.7 generally indicates good predictive power (Bansal et al., 2024). This high R value indicates that the model has successfully internalized the underlying patterns within the data, affirming its capacity to accurately predict outcomes based on ESG scores. Although the validation set yielded a slightly lower R value of 0.590, it still represents a meaningful predictive capability, as values above 0.5 generally indicate moderate to strong correlation (Bansal et al., 2024), demonstrating that the model retains a significant degree of accuracy when applied to unseen data. The validation set is used to assess the model's performance on data it has not been trained on, thereby providing an estimate of its generalization ability. Importantly, the model's performance on the test set, with an R value of 0.736, underscores its strong generalizability, proving its ability to make reliable predictions even when confronted with entirely new data. When considering the combined data, the model achieves an overall R value of 0.706, further reinforcing its efficacy in capturing the intricate relationship between ESG scores and the cost-benefit ratio (CBR). These results collectively underscore the model's robustness and reliability.

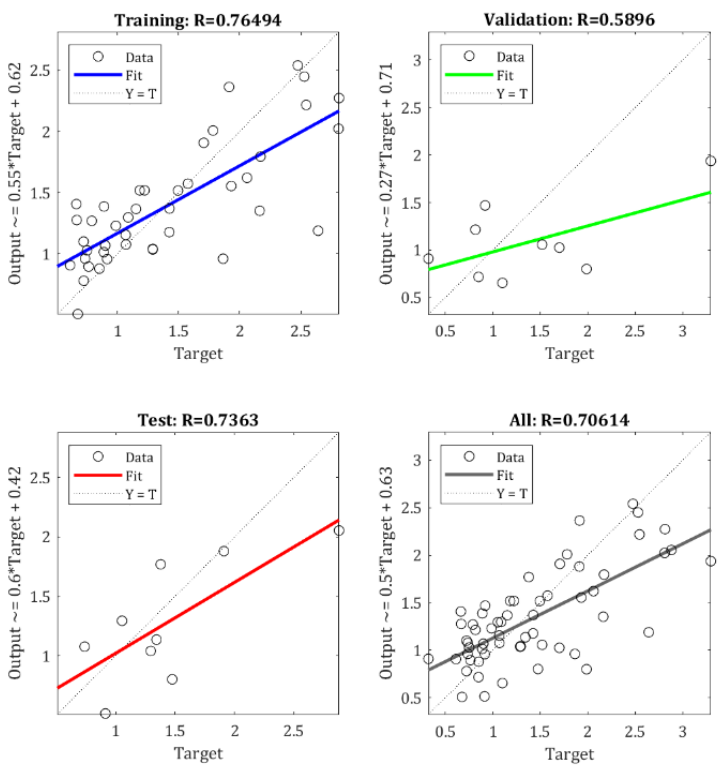

Figure 4: Regression fit for training, validation, test, and all data

3.3 MDP Model Results and Discussions

The contractors’ rewards were calculated using the questionnaire data on ESG implementation and a trained neural network reward prediction model. These rewards, serving as key inputs, were incorporated into the MDP framework to optimize ESG decision-making strategies. The value iteration method was applied to solve the MDP, producing the results visualized in Figure 5. This figure represents state transitions, optimal actions, and their associated rewards. States are depicted as nodes corresponding to different institutional pressure levels, while arrows indicate possible transitions resulting from specific ESG actions. The red arrows highlight the optimal strategies that lead to the highest rewards, with labels indicating the actions taken and their resulting outcomes.

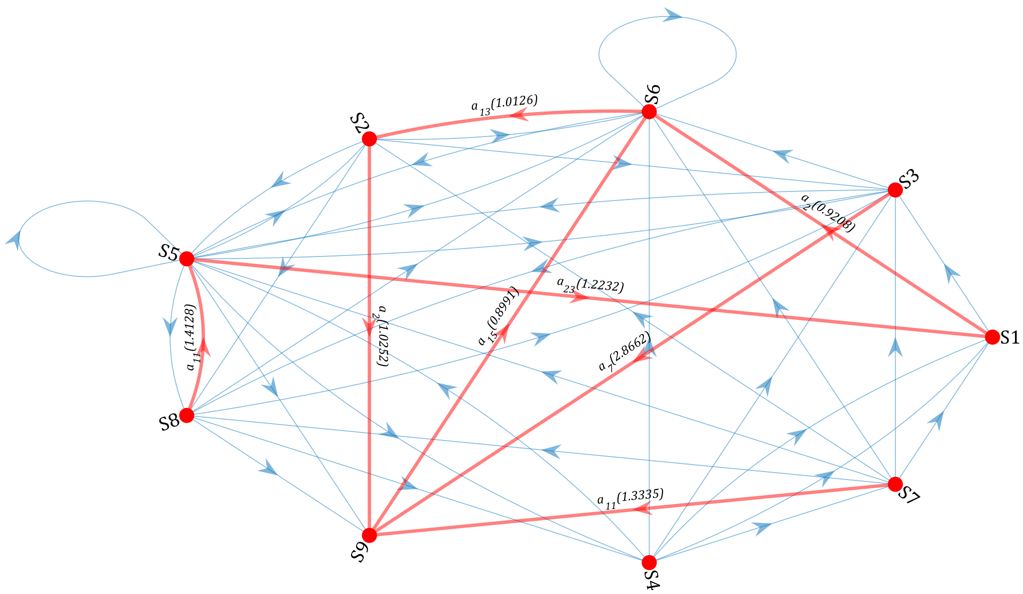

Figure 5: Policy visualization based on MDP

The analysis reveals distinct patterns in optimal ESG strategies across different institutional contexts. In high-pressure environments, such as s_9, where both internal and external pressures are elevated, the optimal strategy involves significant investments across all ESG dimensions. This balanced approach helps contractors manage regulatory and societal expectations effectively. Conversely, in low-pressure environments like s_1, optimal strategies minimize investments in social (S) and environmental (E) dimensions while maintaining steady governance (G) efforts. This strategy ensures compliance and stability with minimal resource expenditure.

Internal pressures significantly influence ESG decision-making. In states with low internal pressures, such as s_1, s_2, and s_3, optimal strategies focus on governance stability while limiting environmental investments. For states with high internal pressures, such as s_7, s_8, and s_9, stronger governance investments are required, alongside moderate environmental and carefully controlled ESG allocations. These strategies address the need for robust governance to maintain operational stability and stakeholder confidence in high-pressure scenarios.

External pressures also play a critical role. In low external pressure states, such as s_1, s_4, and s_7, minimal investments in ESG are advised while maintaining governance as a baseline. In contrast, high external pressure states, such as s_3, s_6, and s_9, require increased ESG investments to address heightened public scrutiny and regulatory demands. ESG emerges as the most flexible dimension, allowing contractors to scale investments based on external conditions while ensuring steady environmental and governance standards.

The model further identifies mid-level pressure states, such as s_5, as intermediaries with diverse incoming and outgoing transitions. These states demand adaptable ESG strategies that reflect their dynamic nature. Governance remains a critical baseline across all states, but ESG investments exhibit greater flexibility, allowing contractors to adjust efforts based on external pressures and public scrutiny.

In summary, the MDP model demonstrates the importance of tailoring ESG strategies to specific institutional contexts. Low-pressure states benefit from governance stability and cost-efficient approaches, while high-pressure states require balanced, multifaceted ESG efforts. The model provides actionable insights into how international contractors can align their ESG initiatives with institutional pressures, optimizing resource allocation and enhancing long-term sustainability and performance.

4 Conclusion, Implications and Limitations

This study developed and applied a Markov Decision Process (MDP) model to identify the optimal ESG strategies for international contractors, determining which actions maximize rewards under varying levels of institutional pressure. The findings suggest that baseline investments in environmental and governance responsibilities are essential across all scenarios for ensuring compliance and organizational stability, while ESG investments remain flexible, allowing contractors to adapt based on external scrutiny and regulatory demands. In low-pressure environments, contractors are advised to focus on operational efficiency with minimal ESG spending, particularly in social and environmental areas, while maintaining governance standards. In high-pressure contexts, however, a more balanced ESG investment across all dimensions is necessary to meet heightened regulatory expectations and sustain operations. This approach enables international contractors to balance compliance, public expectations, and cost-effectiveness, optimizing resource allocation across diverse institutional environments.

This research makes substantial contributions to the application of ESG strategy optimization, particularly under varying institutional pressures, which are central to the decision-making environment in the international construction market. One major contribution is the introduction of an innovative, adaptable framework using a MDP model. This model not only evaluates ESG actions but also deeply integrates the critical influence of institutional pressures, with components like state transitions and reward calculations. This comprehensive approach enables international contractors to tailor their ESG investments to specific types and intensities of pressure, pushing beyond prior studies by emphasizing the role of regulatory and societal dynamics in shaping effective ESG practices. In addition, by uncovering the intricate relationship between ESG investments and resulting rewards, our findings underscore how specific action combinations yield optimal returns, thereby offering contractors a strategic approach to resource allocation that maximizes both efficiency and impact.

The study also offers practical implications for international contractors and businesses operating in complex institutional settings. By identifying the essential role of foundational investments in environmental and governance aspects across all pressure levels, this research provides actionable guidance for sustaining baseline ESG performance. At the same time, it highlights the flexibility of ESG investments, allowing contractors to strategically adjust this dimension based on external scrutiny and regulatory pressures. This structured and adaptable approach to ESG decision-making positions businesses to better navigate evolving ESG demands, optimize performance, and maintain competitiveness in a landscape increasingly shaped by stakeholder expectations and regulatory complexities.

Despite these contributions, this study has several limitations. First, the model assumes complete observability of the institutional environment, which may oversimplify the dynamic and often opaque nature of regulatory landscapes. Future research could address this by incorporating Partially Observable Markov Decision Process (POMDP) to better capture the incomplete or delayed information that often characterizes real-world regulatory dynamics. Second, the model primarily focused on quantitative measures of reward, such as the cost-benefit ratio. Future studies can broaden this scope by incorporating qualitative outcomes, such as reputational impact or stakeholder trust, which are crucial in evaluating ESG performance but more challenging to quantify. Third, although the model is tailored to international contractors, it has broader applicability across industries facing complex ESG demands. Future studies could extend this framework to other sectors, yielding valuable insights into how diverse industries manage ESG integration amid evolving institutional pressures.

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