Automated Incentive Mechanism Design and Testing for Ethereum Ecosystem using Deep Reinforcement Learning

Ethereum Academic Grant Application

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Project Duration: 12 Months
Applicant Type: Academic Institution
Requested Grant Budget: Euro 96,620
Target Wish-list Area: Econ & Game Theory and Humanities

Project Team		
Member	Affiliation	Group Membership
Dr. Ashish Rajendra Sai	Maastricht University	Full Member (Funding Applicant)
Dr. Visara Urovi		
Dr. Harald Vranken	Open University of The Netherlands	Associate Member (no funding required)
Dr. Alan Ransil	Protocol Labs	Associate Member (no funding required)

Abstract

Incentive mechanisms play a crucial role in ensuring that the motives of individual agents are aligned with the goals of a decentralized ecosystem. However, designing effective incentive mechanisms for decentralized agents is a complex problem due to the distributed and unconstrained nature of such systems. Recent research has shown that poorly designed incentive mechanisms can lead to security and market failure issues in blockchain projects. This research proposes a novel framework to simplify the process of designing and testing incentive policies in the Ethereum ecosystem. We propose using a two-level deep reinforcement learning environment to develop and test incentive mechanisms of smart contracts and protocol design decisions in the Ethereum ecosystem. The framework will utilize a reinforcement learning model to automatically learn optimal incentive policies, and simulate the behavior of agents in response to these policies. This framework can provide useful insights into the impact of incentive policies on agent behavior. The utility of the framework is shown with two case studies: developing an incentive policy for a service implemented through a smart contract, and testing the impact of a policy change (transition from PoW to PoS) on wealth centralization in the Ethereum ecosystem. The framework will be documented for use in generic use cases involving incentive mechanism design in the Ethereum ecosystem. The expected outcomes of this project are: (1) advancing academic knowledge on incentive mechanism design and testing for blockchain-based systems; (2) providing practical tools and guidelines for developers and researchers to develop and/or test incentive policies in Ethereum projects.

1 Motivation and Objectives

Ethereum provides a decentralized computing environment capable of executing smart contracts without the assistance of a trusted third party. Popular blockchains including Ethereum and Bitcoin use clever incentive engineering to ensure security (Han et al. 2022). However, designing services implemented through smart contracts and protocols for blockchain-based systems is difficult, as it involves complex trade-offs among multiple objectives such as efficiency, decentralization, security, and sustainability (Azouvi and Hicks 2021; Sai, Buckley, Fitzgerald, et al. 2021).

Blockchain-based systems involve various agents with different roles and interests, such as currency holders, application users, node operators, miners/validators, and protocol developers. These agents may have different preferences, beliefs, and strategies that affect the system outcomes (Hou et al. 2019). Therefore, designing smart contracts and blockchain protocols requires careful consideration of the incentives and behaviors of these agents. Incentive mechanism design is a key component of blockchain-based systems that aims to align the individual agents' interests with the system objectives by devising appropriate rules and rewards.

However, a major challenge in designing incentives in blockchain-based systems is the complexity of the action space for participants. Traditional methods for incentive mechanism design often rely on game theoretical models that assume a stable action space that could be modeled analytically (Azouvi and Hicks 2021). However, this assumption may not hold in blockchain-based systems where the action space changes over time as more blocks are added to the chain, making it hard to apply conventional methods for incentive mechanism design (Eyal and Sirer 2018; Azouvi and Hicks 2021; Sai, Buckley, and Le Gear 2019).

We overcome this limitation by proposing a novel framework for designing and evaluating various incentive mechanisms in a decentralized setting. Our framework leverages a Two-Level deep reinforcement learning environment[1] that can induce alignment between the agents' objectives and the system goals by simulating and optimizing policies. Our prior work[2] has demonstrated the effectiveness of this approach in a Blockchain context, where agent modeling is difficult due to the high-dimensional action space (Pankovska 2022).

1.1 Objectives

The objectives of this project are as follows:

1. To develop a generic framework that implements a Two-Level deep reinforcement learning model for designing and testing of incentive mechanisms in the Ethereum ecosystem. The framework will support the development and testing of multiple incentive policies and quantitative comparison of the policies to streamline the policy testing process.

2. To develop a systematic and rigorous approach to systems modeling for Ethereum and its applications based on widely adopted smart contract standards such as ERC-20 and ERC-721. We will provide comprehensive guidelines that cover the following aspects: (1) the fundamental concepts and principles of systems modeling; (2) the tools and techniques for modeling Ethereum and smart contracts; (3) the best practices and challenges for applying systems modeling in this domain. We will also demonstrate how systems modeling can facilitate realistic simulation models that can be integrated with our proposed Two-Level reinforcement learning framework through examples and case studies.

3. To ground the framework specification and design in real Ethereum-based concerns, we focus on two case studies:

[1] Two-Level deep reinforcement learning (TL-RL) is a novel approach in the field of reinforcement learning (RL) that leverages hierarchical agent structures. In TL-RL, a high-level agent designs incentives for low-level agents, who then optimize their policies based on the incentives. TL-RL has proven effective in complex and dynamic environments (Zheng, Trott, Srinivasa, Naik, et al. 2020).

[2] In Pankovska 2022, we apply a Two-Level reinforcement learning model to design and test green mining policies for Filecoin. Our work also reveals the incentives that storage providers (miners) require to adopt green energy. This research article has directly contributed to the work of the Filecoin Green team.

- **A service implemented on top of Ethereum as a smart contract**: We develop framework specifications to assess the incentive policy of a smart contract[3]. We utilize our prior work on ERC-721 tokens and design policy for the LUCE framework. LUCE is an open and decentralized data-sharing platform for monitoring data re-use in accordance with individual user consent (Urovi et al. 2022).
- **Incentive policy testing for a blockchain protocol**: We apply our framework to evaluate how policy change affects Ethereum itself in the second case study. Previous studies (Sai, Buckley, Fitzgerald, et al. 2021; Sai, Buckley, and Le Gear 2021) have offered a comprehensive overview of wealth concentration in Ethereum, but the influence of policy changes in Ethereum's incentive machine on agent behavior remains unclear. Our framework enables us to examine how the transition from PoW to PoS in Ethereum influences the economic behavior of agents such as currency holders.

4. To disseminate the results and insights of the project to the academic, developer community, and non-technical users through publications, presentations, visualization of incentive policies, and open-source code.

1.2 Achievement Indicators

The success of the project can be measured by the extent to which we can achieve the objectives outlined above. We have provided a more granular breakdown of deliverables of each objective in Table 1:

2 Outcomes

The systematic and automated methodology to designing and evaluating incentive mechanisms will benefit the Ethereum ecosystem. In particular, we provide a tool to improve the efficiency, decentralization, and security of various applications and protocols built on Ethereum.

The project will create guidelines for developing conceptual models of systems within the Ethereum ecosystem. These guidelines will assist developers and researchers to better document their modeling choices and trade-offs. Consequently, this will improve the understanding of the limitation of these reductive models and provide a much-needed mechanism for understanding, analyzing, and documenting the complex operational aspects of developing and deploying smart contracts and blockchain platforms. These models can also be utilized within our generic framework to automatically design and test incentive mechanisms.

[3]Incentive policies for platforms using smart contracts lack formal development. Recent posts on ethresear.ch suggest a need for more rigorous methods to design and test these policies. See `https://ethresear.ch/t/using-simulations-to-optimize-cryptoeconomic-parameters/2406` for more details.

Objective	Achievement Indicators	Measures
1. Framework Development	Completeness of the framework (for both services built on top of Ethereum and the Ethereum network itself)	Well documented, functional code for both the indicated purposes shared on a public repository on Github
	Quality of code and User-friendliness	Sufficient fulfillment of essential software quality metrics as listed by Kan 2003
2. Guidelines for modeling	Comprehensiveness, effectiveness and applicability of the guidelines	Calibration of the developed models through existing datasets, soliciting feedback from experts and practitioners and testing the guidelines against the two case studies
3. Case Studies	Comparable or better policies designed for both case studies	Comparing the policy designed by the system to the one proposed by LUCE system (Jaiman, Pernice, and Urovi 2022). In the second case study, we compare the resulting agent behavior with the transactional data from the Ethereum blockchain.
4. Dissemination	Number and quality of publications, presentations and the level of engagement with the Ethereum community	At least 1 publication at a reputed academic venue (journal or conference), contribution to ETH organized devcons where appropriate, development of interactive visualisation to assist non-technical users understand what incentive mechnisms are and how they function

Table 1: Objectives and achievement indicators

This project advances academic knowledge on incentive mechanism design for blockchain-based systems. By using deep reinforcement learning as a tool to automatically learn optimal incentive policies, the project will leverage state-of-the-art machine learning techniques. By simulating the behavior of agents in response to the policies, the project will capture a diverse set of scenarios that may arise in real-world settings. By conducting case studies on service provision and wealth centralization in the Ethereum ecosystem, the project will address relevant and important issues that affect the security and decentralization of the Ethereum ecosystem.

For example, in the first case study, the project will design incentive mechanisms for a decentralized data-sharing platform that rewards data providers and data consumers for engaging in data-sharing. This ensures that data is exchanged and utilized in accordance to the data sharing protocols. In the second case study, the project will simulate how different types of agents (currency holders, application users, application users, node operators, miners/validators, and protocol developers) react to the transition from proof-of-work (PoW) to proof-of-stake (PoS) consensus mechanism in Ethereum 2.0 (Buterin et al. 2020). This helps us to understand how this policy change affects wealth distribution and centralization in the ecosystem, and whether it creates any unintended consequences or incentives for malicious behavior. This can also inform future policy decisions and adjustments by ensuring an adequate understanding of their impact on aspects such as decentralization.

We will document the framework to be of use in generic use cases involving incentive mechanism design in the Ethereum ecosystem. To accomplish this, we will provide practical tools and guidelines for developers and researchers who want to apply the framework to their problems or scenarios. Thus Ethereum developers will be able to design more effective and efficient incentive mechanisms that suit their specific needs and objectives.

The project will also provide tools to visualize the incentive policies generated by the proposed framework. This visualization will assist non-technical users to understand the functions and limitations of incentive policies used by Ethereum-based projects.

3 Grant Scope

3.1 Research Scope

The goal of this project is to assist in the process of developing and testing incentive policies within the Ethereum ecosystem. We intend to accomplish this by developing a novel framework consisting of tool kits and guidelines for automated incentive mechanism development and testing using a two-level deep reinforcement learning modeling. The framework will consist of two levels: a policy learning level that will use deep reinforcement learning algorithms to find an optimal incentive policy for a given objective function; and a simulation level that will model the behavior of agents (e.g., currency holders, application users, application users, node operators, miners/validators and protocol developers) in response to this incentive policy. The framework will be able to handle different types of objectives (e.g., social, revenue, fairness) and constraints (e.g., decentralization, privacy, security) in designing incentive mechanisms. The framework will also be generalized and documented to apply to any generic use case involving incentive mechanism design in the Ethereum ecosystem.

To demonstrate the usefulness and effectiveness of the framework, we will conduct two case studies: one on developing an incentive policy for a service implemented through a smart contract (Urovi et al. 2022); and another on testing the impact of a policy change (move from PoW to PoS) on wealth centralization in the Ethereum ecosystem (Sai, Buckley, and Le Gear 2021). We will also analyze and document the trade-offs and challenges involved in applying our framework to real-world scenarios.

3.2 Research Outcomes

The expected outcomes of this project are:

1. **Systems modeling guidelines**: A comprehensive guide on systems modeling for Ethereum and smart contract services, including basic concepts, tools, techniques, best practices, and real-world examples. This guide will demonstrate how systems modeling can be used with the Two-Level reinforcement learning framework proposed by the research work to design efficient smart contract systems.

2. **Framework for designing and testing incentive mechanism**: This outcome will provide a novel method for designing and testing incentive mechanisms that can adapt to complex environments and preferences of agents in the Ethereum ecosystem. The framework will leverage state-of-the-art deep reinforcement learning techniques to learn optimal incentive policies, without requiring prior knowledge or assumptions about the agents' behavior or utility functions beyond a fundamental systems model. The framework will also incorporate different types of objectives and constraints that are relevant for incentive mechanism design in the Ethereum ecosystem, such as social, economic, decentralization, privacy, and security.

3. **Two case studies demonstrating the usefulness of the framework**: We will demonstrate how our framework can be applied to real-world problems and scenarios in the Ethereum ecosystem. The first case study will focus on developing an incentive policy for a service implemented through a smart contract, such as a decentralized data sharing system (Urovi et al. 2022). The second case study will focus on testing the impact of a policy change (move from PoW to PoS) on wealth centralization in the Ethereum ecosystem (Sai, Buckley, and Le Gear 2021; Sai, Buckley, Fitzgerald, et al. 2021).

4. **A generalizable and documented software tool based on our framework**: This outcome will provide a practical tool that can be used by developers and researchers working on Ethereum-related projects to design and test incentive mechanisms for their use cases. The tool will be generalizable to any generic use case involving incentive mechanism design in the Ethereum ecosystem. The tool will also be documented with clear instructions, examples (specifically utilizing outcome 3), and tutorials on how to use it.

4 Project Team

Dr. Ashish Rajendra Sai

Dr. Sai is a Lecturer/Assistant professor at Maastricht University and The Open University of The Netherlands. He has a Ph.D. in Computer Science from SFI Centre for Software Ireland where his research focused on better understanding what decentralization entails in a blockchain context.

Dr. Sai's research on the blockchain has been featured in several national and international media outlets (Forbes, Economic Times). His work on centralization has been foundational to policy development around cryptocurrencies. SEC in the US has used Dr. Sai's work as a part of arguments in the case against Ripple. Outside the US, Dr. Sai's work has been cited by OECD, Ada Lovelace Institute, and Norges Bank in their policy documents.

He has also worked as visiting scholar at the University of California, Berkeley where he continued working on promoting scientific rigor in blockchain research. In the past, he has worked as a lecturer at Trinity College Dublin and the University of Amsterdam where he supervised several theses on blockchain-related topics.

His research focuses on blockchain, smart contracts, incentive mechanism design, and reinforcement learning. Some of his publications include:

- Taxonomy of centralization in public blockchain systems: A systematic literature review
- Assessing the security implication of Bitcoin exchange rates
- Characterizing wealth inequality in cryptocurrencies
- Promoting Rigour in Blockchains Energy & Environmental Footprint Research: A Systematic Literature Review

The role for this project: Principle Investigator Time commitment per month: 16 hours

Dr. Visara Urovi

Dr. Visara Urovi is an associate professor at the Institute of Data Science at Maastricht University. Dr. Urovi focuses on privacy-preserving decentralised health data exchange and analysis. She is the primary investigator of the PRIMA project, a blockchain-based solution focusing on health data exchange. Dr Urovi has proposed LUCE, an open-source blockchain platform for monitoring data licenses (github.com/arnoan/LUCE) and is involved in multiple National and International projects on health data sharing and analysis such as REALM (https://realm-ai.eu/). Previously she held a postdoc position at the University of Applied Sciences of Western Switzerland, where she was working on eHealth platforms and interoperable health data exchange. In 2010 she obtained her PhD degree in Computer Science from Royal Holloway University of

London. She holds a MSc and a BSc in computer Engineering from University of Bologna.

The role for this project: Research Supervisor (Co-PI) Time commitment per month: 8 hours

Associate Members

Dr. Harald Vranken

Dr. Harald Vranken is an associate professor at the Open University of the Netherlands and the Radboud University. He has a Ph.D. in computer science from the Eindhoven University of Technology and has worked on various topics such as software engineering, information security, and the sustainability of information technology.

Dr. Vranken is one of the leading experts on the energy consumption of bitcoin and its environmental impact. His seminal work on the sustainability of blockchain is frequently cited by government policies such as the recent white house policy on cryptocurrencies. His current research focuses on the sustainability of bitcoin and blockchains. He has published several articles on this topic in academic journals such as Current Opinion in Environmental Sustainability and IEEE Security & Privacy.

Dr. Alan Ransil

Dr. Alan Ransil is the team lead for Filecoin Green at Protocol Labs, a project building web3 tools to track and verify carbon emissions. He has worked in sustainability and renewable energy since 2008 as an academic researcher, product manager, and startup co-founder. He holds a PhD in Materials Science and Engineering from MIT, where he studied structural batteries for transportation and worked on projects for the MIT Energy Initiative, ARPA-E, and DARPA.

During graduate school he co-founded CoolComposites, a company aimed at producing thermally active materials to reduce the energy needed to cool buildings. At Protocol Labs he studied decentralization in power grids and developed a model for determining the energy use of the Filecoin blockchain. In his current role he is also an organizer for the Sustainable Blockchain Summit, a recurring conference aimed at promoting verifiable sustainability claims.

5 Background

Our research is motivated by prior work on developing and testing incentive policies for blockchain-based systems. Azouvi and Hicks 2021 in their SOK article indicate that the current landscape of game theoretical models used for formal analysis of incentive policies is restrictive due to the constraints of reductive game theoretical models. Some recent work such as Hou et al. 2019 has provided some potential avenues for circumventing these limitations through the use of reinforcement learning within a blockchain context.

Outside the blockchain domain, several researchers have proposed to use machine learning techniques, especially deep reinforcement learning (DRL), to automate and improve the design of incentive mechanisms for complex socio-economic systems (Zheng, Trott, Srinivasa, Naik, et al. 2020; Zheng, Trott, Srinivasa, Parkes, et al. 2021; Trott et al. 2021; Strouse et al. 2021; Lavin et al. 2021; Koster et al. 2022). For example, Salesforce Research has developed an AI framework called The AI Economist that uses DRL to learn optimal tax policies for improving social welfare in a simulated economy (Zheng, Trott, Srinivasa, Naik, et al. 2020). Similarly, some practitioners within the Ethereum ecosystem have suggested using simulations to optimize crypto-economic parameters, such as block rewards or transaction fees, that affect the behavior and outcomes of agents in blockchain networks [4].

Despite the recent advancements in using reinforcement learning, specifically a Two-Level reinforcement model, there is still a lack of a general framework for applying DRL to incentive mechanism design for smart contracts and protocol design decisions in the Ethereum ecosystem. Our prior work has utilized this Two-Level reinforcement learning approach to develop an incentive policy for sustainable mining in the Filecoin network[5]. The output from our prior has been used by the Filecoin Green team [6] to fine-tune their reputation score system.

We have also published numerous articles exploring incentives for blockchain systems (Sai, Buckley, Fitzgerald, et al. 2021; Sai, Le Gear, and Buckley 2019) and smart contracts (Urovi et al. 2022; Jaiman, Pernice, and Urovi 2022). Our research experience in both applied and fundamental research within the blockchain domain feeds into our proposal to develop and test a generic automated framework for incentive mechanisms.

A subset of related research papers for review:

- Elitsa Pankovska (2022). "Determining Optimal Incentive Policy for Decentralized Distributed Systems Using Reinforcement Learning". University of Amsterdam[7]

- Elitsa Pankovska, Ashish Rajendra Sai, and Harald Vranken (2023). "Determining Optimal Incentive Policy for Filecoin Using Reinforcement Learning". In: *IEEE International Conference on Blockchain and Cryptocurrency (ICBC)*

- Stephan Zheng, Alexander Trott, Sunil Srinivasa, Nikhil Naik, et al. (2020). "The ai economist: Improving equality and productivity with ai-driven tax policies". In: *arXiv preprint arXiv:2004.13332*

- Michael Mainelli, Matthew Leitch, and Dionysios Demetis (2019). "Economic Simulation Of Cryptocurrencies & Their Control Mechanisms". In:

[4]https://ethresear.ch/t/using-simulations-to-optimize-cryptoeconomic-parameters/2406

[5]https://www.filecoin.com/

[6]https://green.filecoin.io/

[7]The full text of this thesis is available online at the following link: https://ashishrsai.github.io/Ellie_Thesis.pdf.

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- Charlie Hou et al. (2019). "SquirRL: Automating attack analysis on blockchain incentive mechanisms with deep reinforcement learning". In: *arXiv preprint arXiv:1912.01798*
- Vikas Jaiman, Leonard Pernice, and Visara Urovi (2022). "User incentives for blockchain-based data sharing platforms". In: *Plos one* 17.4, e0266624

Some ralvent gray litertaure disucssions:

- Ethereum Research Forum, Tim Beiko, and Cameron Pfiffer, "Using Simulations To Optimize Cryptoeconomic Parameters", `https://ethresear.ch/t/using-simulations-to-optimize-cryptoeconomic-parameters/2406`
- IncentiveAI, Piotr Grudzien, "Simulation of the Augur economy", `https://medium.com/incentivai/simulation-of-the-augur-economy-682636d2840f`
- IncentiveAI, Piotr Grudzien, "Bonding curve simulation for Ocean Protocol", `https://medium.com/incentivai/bonding-curve-simulation-using-incentivai-2b2bfe0c6400`
- IncentiveAI, Piotr Grudzien, "Analysis of the Nexus Mutual smart contract system", `https://medium.com/incentivai/incentivai-analysis-of-the-nexus-mutual-smart-contract-system-a9f8a1ac7c47`

6 Methodology

In this section, we outline the steps that will be taken to achieve the objectives of this project (as listed in the objectives). We have segmented our approach into 4 phases are illustrated in Figure 1.

In phase 1, we develop an initial version of best practices for modeling services based on Ethereum and the protocol itself. This initial version feeds into phase 2, where we develop a Two-Level Deep RL model for Ethereum. Based on the calibration of this model, we iteratively revise the best practices from phase 1. Once a reliable model is developed, we move to phase 3, where we conduct the two case studies outlined in Grant Scope and Objectives. All of these three phases feed into our dissemination package (defined as phase 4). We have provided a brief overview of all four phases below:

6.1 Phase 1: Guidelines for Modelling

To develop the guidelines for modeling, we conduct a literature review. In the literature review, we will review the basic concepts and principles of systems modeling, such as system elements, relationships, boundaries, inputs, outputs, and feedback loops (Pidd 2004).

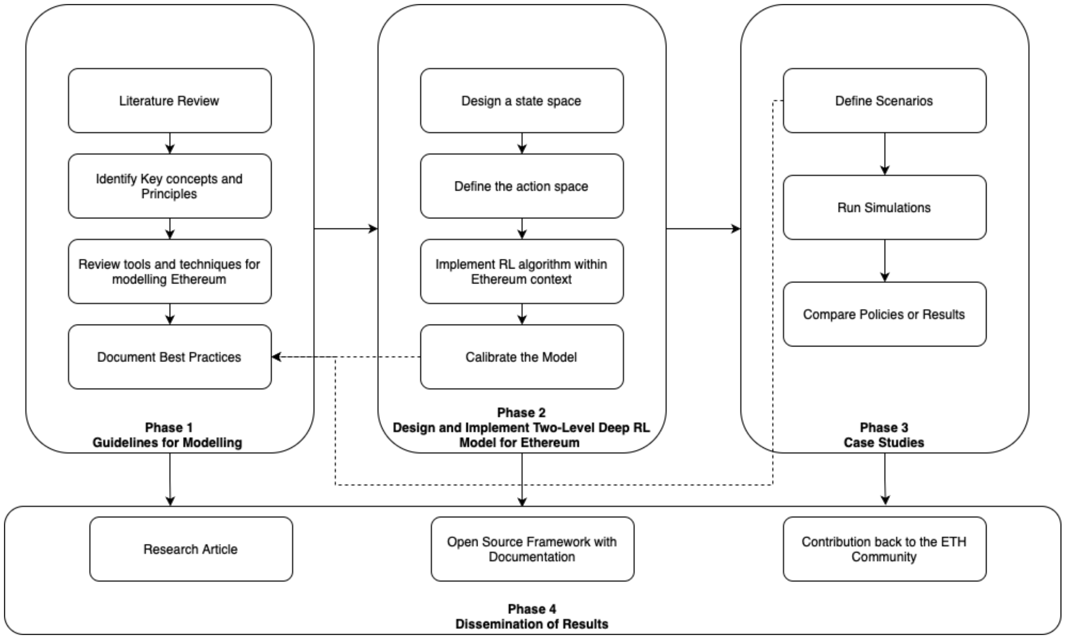

Figure 1: 4 Phases of Framework Development

To identify the key concepts and principles for system modeling concerning Ethereum, we will review existing case studies of systems built on top of Ethereum as well as a formal analysis of the Ethereum network itself[8]. After identifying key components of the system's design for Ethereum, we will examine possible tools and techniques that could be applied in the context of Ethereum. This will also feed into the development of best practices.

6.2 Phase 2: Design and Implementation of Two-Level Deep RL Model for Ethereum

A two-level deep reinforcement learning model will be designed and implemented using Python and deep learning libraries such as TensorFlow or PyTorch. The model will consist of two agents: an incentive policy agent and a simulation agent.

The incentive policy agent will be responsible for learning optimal incentive policies using deep reinforcement learning techniques. The agent will receive information about the state of the system, such as transaction information, gas prices, and other relevant data. The agent will then use this information to take actions that maximize a reward function that reflects the desired incentive outcome of the smart contract or protocol design decision.

[8]There is a wealth of literature that focuses on formal analysis of blockchain network such as Laneve and Veschetti 2020; Silveira et al. 2021

The simulation agent will be responsible for simulating the behavior of agents in response to the learned policies. The agent will receive information about the state of the system, such as transaction information and user behavior. The agent will use this information to simulate the response of agents to the learned policies and provide feedback to the incentive policy agent.

To achieve this we will follow the steps outlined below:

1. Determine the state space: The state space is the set of all possible states of the system under consideration. For this project, the state space will include information on the relevant components of the Ethereum blockchain.

2. Define the action space: The action space is the set of all possible actions that an agent can take in a given state. In this project, the action space will consist of the available options for setting incentive mechanisms for smart contracts and protocols in the Ethereum ecosystem for the incentive policy agent and a user-defined space for the simulation agent.

3. Implementing PPO within an Ethereum context: In line with the suggestions of Zheng, Trott, Srinivasa, Naik, et al. 2020, we will implement a Proximal Policy Optimization (Schulman et al. 2017) for use within an Ethereum ecosystem context.

4. Calibrate the model: The model will be calibrated using historical data from the Ethereum blockchain. The data will be preprocessed to extract the relevant features and encode them into a format suitable for input into the implemented algorithm.

6.3 Phase 3: Case Studies

To evaluate the performance of the two-level deep reinforcement learning model, the model will be tested on different scenarios, including the two case studies mentioned in the project overview: (1) developing an incentive policy for a service implemented through a smart contract and (2) testing the impact of a policy change (move to PoS) on wealth centralization in the Ethereum ecosystem.

The model will also be compared with existing incentive mechanisms to evaluate its performance[9]. The evaluation metrics may include the efficiency of the incentive mechanism, the impact on wealth distribution, and the security of the smart contract or protocol design decision.

To achieve this objective, the following steps will be taken:

1. Define the scenarios: Scenarios will be defined to test the model's applicability in different incentive scenarios.

2. Run the simulations: The model will be run on the defined scenarios, and the performance of the model will be evaluated in terms of its ability to optimize the incentive mechanisms.

[9] For the LUCE platform, our existing work has provided extensive documentation of incentive policies (Jaiman, Pernice, and Urovi 2022)

3. Compare with existing incentive mechanisms: The results from the simulations will be compared with the performance of existing incentive mechanisms and theories on the motivation behind agent behavior. This will provide insight into the potential usefulness of the proposed framework.

6.4 Phase 4: Dissemination of Results

To disseminate the results and insights of the project to the academic and developer community, we intend to publish a paper in a reputable academic journal and present findings at relevant conferences. The paper will describe the methodology, experimental setup, and results of the project in detail.

The project code will also be open-sourced on a publicly accessible code repository to enable other researchers and developers to use and build upon the framework. The repository will include documentation, code samples, and tutorials to help users understand and use the framework.

7 Timeline

The proposed project has a timeline of 12 months, which will be divided into two milestones. Each milestone will have a set of specific deliverables that will be achieved during that period. The two milestones and their respective deliverables are as follows[10]:

- **Milestone 1** (*Month 1 - Month 6*): During this period, we will conduct an extensive literature review to develop modeling strategies for the Ethereum ecosystem. We will also design and implement a two-level deep reinforcement learning model for incentive mechanism design in the Ethereum ecosystem.

  The deliverables for this milestone will include a detailed guideline on designing models with documentation of best practices based on the state of the art in academic and gray literature and a working prototype code with documentation.

- **Deliverables**:

  - **D1**: Research report on the state of the art in modeling Ethereum's ecosystem including smart contracts and the protocol itself. With guidelines on best practices from cognizant domains of system modeling (such as information systems).
  - **D2**: A functional prototype codebase with well-documented code and clear instructions for how to use and customize the model. The documentation will also include a clear overview of the two-level model architecture.

[10]We have also included a task-wise resource allocation table in Appendix A.

- **Milestone 2**(*Month 7 - Month 12*): During this period, we will calibrate and test the model on different scenarios using the selected case studies. We also intend to make our research more accessible to both technical and non-technical users of Ethereum by developing visualization tool for our framework. The deliverables for this milestone will include a trained and tested model with documentation.

- **Deliverables:**
  - **D3**: Code and instructions for how to run simulations using the model and test its performance in different scenarios. With a report detailing the model's training process, any obstacles that were encountered and resolved during training, and the model's validation results
  - **D4**: An open-source code repository with an appropriate license that allows the broader research, development and non-technical users to make use of the project's findings and tools.

  By the end of the 12-month timeline, we expect to have achieved all four milestones and delivered all the required deliverables. This will allow us to accomplish our research objectives, advance academic knowledge on incentive mechanism design for blockchain-based systems, provide practical tools and guidelines for developers and researchers working on Ethereum-related projects, and contribute to the decentralization, security, and sustainability of the Ethereum ecosystem.

8 Budget

The requested grant amount for this project is **Euro 96,620.83**. The breakdown of how this will be used is as follows:

Cost Element	Description	Time Commitment	Cost
Principle Researchers	Dr. Ashish Rajendra Sai	16 Hours per month	Euro 10,945.14
	Dr. Visara Urovi	8 hours per month	Euro 8,078.74
Other Staff Costs	Research Engineer	Full-Time (1 FTE)	Euro 73,596.95
Hardware Costs	NA	NA	NA
Software Costs	We intend to use open source software where required	NA	Euro 0
Indirect Costs	For travel expenses, conference fees, publication fees	NA	Euro 4,000
Total			**Euro 96,620**

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A Resource Allocation

Task #	Name / Title	Type	Start Date	End Date	Resources
1	ETH_RL	project	Month 1	Month 12	
1.1	Phase 1	group	Month 1	Month 6	
1.1.1	Literature Review	task	Month 1	Month 2	Research Engineer
1.1.2	Identify Key concepts and principles	task	Month 2	Month 2	Research Engineer, Ashish Sai
1.1.3	Review tools and techniques	task	Month 2	Month 3	Research Engineer
1.1.4	Document Best Practices	task	Month 3	Month 4	Research Engineer, Visara Urovi, Ashish Sai
1.2	Phase 2	group	Month 4	Month 6	
1.2.1	Design and Develop the RL Model	task	Month 4	Month 5	Research Engineer
1.2.2	Calibrate the Generic Model Framework	task	Month 5	Month 6	Research Engineer, Visara Urovi, Ashish Sai
1.2.3	Milestone 1	milestone	Month 6	Month 6	Research Engineer, Visara Urovi, Ashish Sai
1.3	Phase 3	group	Month 7	Month 12	
1.3.1	Define Scenarios for case studies	task	Month 7	Month 9	Visara Urovi, Harald Vranken, Alan Ransil, Research Engineer, Ashish Sai
1.3.2	Run Simulations	task	Month 9	Month 10	Research Engineer
1.3.3	Compare Policies or Results	task	Month 10	Month 12	Research Engineer, Visara Urovi, Ashish Sai
1.4	Phase 4	group	Month 4	Month 12	
1.4.1	Research Article	task	Month 10	Month 12	Alan Ransil, Harald Vranken, Research Engineer, Visara Urovi, Ashish Sai
1.4.2	Open Source Framework Documentation	task	Month 4	Month 6	Research Engineer, Ashish Sai
1.4.3	Contribute back to the ETH Community	task	Month 6	Month 12	Visara Urovi, Alan Ransil, Harald Vranken, Research Engineer, Ashish Sai
1.4.4	Milestone 2	milestone	Month 12	Month 12	