Automation mechanisms for market models

Case study to reduce cultural discrimination in energy trading

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Case study to reduce cultural discrimination in energy trading

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An electronic version of this thesis is available at `http://repository.tudelft.nl/`.

The codes for the thesis are available at `https://github.com/rhythimashinde/EnergyVCG`

Source of the cover image `http://bit.ly/2noY4Ul`

Preface

The thesis is aimed for readers who are interested in understanding the impact and minimizing the impact of cultural and social behaviors of community on small local energy markets. To understand this impact, the agent based models are developed for different types of markets which are possible for energy trade. To minimize the impact of culture on the trade, different mechanisms are introduced in the trading, e.g. presence of a mediator during trade to overlook any form of discrimination among agents. The chapter 1 will be able to outline these problems in depth.

The readers are expected to have a basic understanding of social science or systems modeling and basic mathematics. The Chapter 2 would be helpful to gain or build up on this knowledge of different types of market models and their details. The readers who have a clear understanding of market models can skip this chapter and go through chapter 3-4 to understand how different literatures are combined to develop the models and its design, followed by the experiments.

The readers who are interested in only the results, can simply read through chapter 6 and in case of doubts on the results, simply refer back to how the model was implemented as described in Chapter 5. The final conclusions and discussions of the thesis are given in Chapter 7. The models, data and the codes can be found on the github links given on the title page of the thesis. The language throughout the thesis is kept very simple for readers with basic understanding of mathematics and statistics.

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1 Introduction

1.1. Energy trading discrimination

India has over 200 million people still without electricity and 85% of these households are from rural India. The definition of electrified village here is simply a village with all the houses connected to grid. Government schemes have focused on only the electrification of villages and not focused on electrification from house-to-house. This has not allowed every house in villages to be electrified, preventing from 100% electrification. In spite of more villages getting electrified (78%), very few of them have all of the households electrified in last 2 years (8%) [62].

There are many decentralization solutions possible to solve the issue of electrification due to problems with centralized sources. The centralized solutions are usually the large thermal or hydro power plants. The problem with the centralized solutions include the power losses of the distribution companies (DISCOMs), rough terrains, and patchy (distributed) remote settlements in rural areas [12]. The solar based decentralized electrification has been the primarily focus of government and projects because of the solar potential of India amounting to 750 GW [73], better storage options, portability and variety in production and installation, and significant drop in solar tariff rates (due to advancing technologies e.g. better efficiency of panels) [37].

Decentralization solutions are mostly common in the form of solar home systems (SHS) or rooftops with integrated solar Photo-Voltaic(PV) panels, batteries, optional inverters, charge controllers and devices (usually, LED lamps). These rooftops can be connected to each other for trading/sharing of energy between the households in case of excess of energy produced for one house and more energy needed at another. The problems with all these solar electrification projects lie in their sustenance i.e. long term project life which is for at least 10 years and includes two life spans of batteries. These projects are susceptible to changing factors across time and region among the community, or the project properties. These factor include the socio-cultural factors e.g. trust, economic factors e.g. income disparity, desires/demands of the community and the technical factors e.g. better batteries, smaller PVs. [28, 72, 77, 79].

The Indian context is already well studied by several studies on factors leading to success and failure of these rural electrification projects is already carried out[6, 13, 17, 58]. This research focuses on the presence of economic barriers as one of the major causes of the energy affordability. For example, one study has shown that how the factors like trust in community change the complete mechanism of “sharing" of electricity in villages. The castes or the sections of community which did not trust each other due to historical disputes, were not ready to share energy [72]. As a solution, figuring out more efficient off-grid and solar lights distribution policies in form of priority to certain economic sections of society has been suggested [19, 54].

Focusing more on the social and cultural factors which affect a project include the careful choice of target users, identification and appointment of a local leader who people trust on, and who is usual decision maker in a community. Community participation right from the installation of the projects has shown to affect the choice of people to trust in the technology or not [79]. The institutional factors like the presence and absence of democracy showed to make a major difference in deciding success of rural electrification projects [77]. Some institutional framework changes like engaging consumers and municipalities while considering the low paying capacity of rural dwellers at national level, proved to be helpful in some cases like Morocco [56]. Study based in Uganda showed that how identifying the right needs of a community based on their values helps in success of these projects [28].

Thus, though these projects might be technically feasible, but due to economic, social-cultural factors, they may not be always socially acceptable. To understand if an electrification project is successful in all aspects, a project should have affordability, accessibility, reliability to the consumers, and profitability to the producers. The success parameter of affordability brings the most attention here due to high poverty being one of the major reasons for lack of electrification in rural India [59]. One of the solutions here is sharing of solar energy as per daily demands which can be easily afforded than a monthly payment.

Sharing of energy is difficult in rural areas as everyone in the community is not very open to sharing resources due to the discriminations in the community [71]. The assumed discrimination of the caste systems are that the villages are composed of caste-homogeneous segregated neighbors: Upper caste is not willing to buy resources from lower castes, but it is okay with selling. Upper castes are wealthier, thus consume and produce more than lower castes [46, 52].

These claims were also validated based on the empirical study in the fields and with the experts' interviews[1]. The experts from nine different projects based in India confirmed that there is existing discrimination in energy sharing. There is enough evidence in the literature for public and natural resource discriminations in the community. Note that all these literature are also based on empirical analysis. Some literatures discuss the consequences of these discriminations on resource sharing emphasizing that only people within same socio-cultural group exchange goods ("selectivity in allocations against Muslims and scheduled castes")

[1] `http://bit.ly/thesis-policy-analysis-shinde`

[5, 11, 41, 50, 51, 76].

1.2. Problem statement

Existing solutions for these problems are based on modeling the resource sharing as transaction among the users, or conflict management. Here the users are assumed as "agents". The transactions of the agents get influenced from the socio-cultural (castes, religions, etc.) and/or economic parameters (motives for profits, income level, etc.). Some of the literatures into the transaction and conflict management also emphasize on these discriminating characteristics of the community (presence of informal discrimination regulations). The models which can simulate such user (agent) behaviors in form of transactions in a market setting (environment) are called agent based models and these are discussed further.

Across literatures there are many works done notably by Kirman in the financial market and goods exchange e.g. fishes, for understanding different types of market setting, buyers and sellers behavior. This involves developing agent based models where every seller and buyer acts according to market rules e.g. bids 24 times in a day with the price and quantity of the good it needs or wants to sell. Either agents optimize their own utility functions e.g. maximizing profits or maximize utility of the market consumers needs [7, 38, 69, 78]. Different bidding and acceptance strategies in electricity markets are employed by the agents and involve bidding as per memory or trust i.e. number of times the buyer and seller meet in market [45, 53, 81]. In this process of exchange, agents also learn about the other agents and changes their behavior via different methods e.g. comparing its own profits with other [14, 22]. Most of the price matching is done via a passive role of buyer in the market where seller decides a price [43]. Though they are other methods discussed around uncertainty in the market and bidding strategies as well [7, 69]. Finally the different simulation settings as discussed in these literatures help in defining experiments which are compared based on different evaluation measures like social welfare, efficiency, etc. of the energy exchange [38, 64].

All these different mechanisms explained in the above paragraph cover different aspects of agent based modeling. But none of them is used for the context with the cultural and social implications of a community as in the chosen context of this research. The energy sharing from peer to peer i.e. in a bilateral market is also a new context which is not clearly researched upon in energy trading and thus the aim of this research is to fulfill these gaps.

1.3. Research goals and contributions

Based on the above description of the energy markets and existing market models, there are some important problems in the context of energy sharing in India. We decide to tackle them by means of Agent based models. These opportunities and problems allow to test different mechanisms of mediated and non-mediated energy trading for reducing the discriminations in energy trading to facilitate fairer local energy markets. It also allow to incorporate better understanding of markets and seller-buyer behavior from the financial markets to apply for peer to peer energy trading market. Finally, learnings from cultural models for testing effect of socio-cultural factors on the trading market can be incorporated in the models.

Thus the goal of this research is to improve efficiency in energy sharing in presence of social discrimination and eventually reduce discrimination. Based on this goal, the research question for this thesis is: *"How different mechanisms affect reduction of discrimination and optimizing efficiency in the setting of energy trading in rural India?"*

1. What are issues with existing solutions with respect to discrimination and efficiency in energy trading?
2. What cultural models and market models fit best to the current scenario, capturing trade-offs in efficiency and discrimination?
3. How do different models perform for the measures of efficiency and discrimination?

The methodology for answering these research questions is shown in Table 1.1. The first step for answering the overarching research question is to develop an architecture which can help define mechanisms to test the effects of discrimination and efficiency in energy trading. This step involves defining structure of the agents and the environment for the agent based models. After this, the bidding and acceptance strategies for the agents are introduced. The next step is to detail out this design of agents to implement the models based on the financial trading, energy market and Indian context. To test these effects, experiments are conducted to compare and evaluate different agent based models. Each of these methods will be introduced in this chapter briefly.

Table 1.1: Research Question to methodology

	Questions	Methodology	Chapters
1	What are the issues with the existing solutions with respect to discrimination and efficiency in energy trading?	Literature Review of models around trading with cultural influences	Ch 1 and 2
2	What cultural models and market models fit best to the current scenario, capturing trade-offs in efficiency and discrimination?	Design agent based models based on literature	Ch 3 and 4
3	How do different models perform for the measures of efficiency and discrimination?	Perform experiments based on the evaluation measures on the models	Ch 5 and 6

Based on these questions, the main contributions of this thesis are meant to be societal as well as in the computer science research, and they are:

1. Development and implementation of a general simulation framework i.e. agent based models for bilateral and mediated bid matching.
2. Implementation of cultural effects as cultural models on the designed framework for agent based models for bilateral and mediated bid matching.
3. Introduction and implementation of bid splitting mechanism to reduce influence of culture i.e. discrimination among agents.
4. Definition and implementation of evaluation measures for culture affected agent based market models.

1.4. Thesis outline

After the introduction in this chapter, the thesis is laid out as follows: Chapter 2 lays down the state of art on the agent based modeling for different types of markets. Chapter 3 lays down the chosen methodology for this research as per the research question. This chapter also lays down an introduction to experiments, model choices and the evaluation criteria for the thesis. Chapter 4 discusses the designed models and the agents' structures. Chapter 5 goes into the depth of the design of the agent based models and the experiments. Chapter 6 compares the results from the implemented models. Chapter **??** discusses the results and the approaches and reflects on how the approaches influenced the result and what can be improved further. Finally, chapter 7 lays down the final conclusions from the model, followed by recommendations and further research steps recommended to carry out in this research.

2

Literature Review

The focus of this thesis is on a market which can satisfy prices and quantity (energy market). Focusing on the prices, literatures discuss agent based models in financial markets. Section 2.1 discuss the methodology used for the literature review and the section 2.2-2.6 discuss these literatures.

Agent based models for financial markets are in two broad categories: qualitative and quantitative models, where the former stresses on testing out hypothesis/ abstract ideas by means of computer based simulations. The latter tackles calibration to real data or even forecasting. The focus of this thesis would be more on a qualitative model where certain hypothesis based on the energy market would be tested. Focusing on the quantity or the energy market, majority of these models have a game-theoretic approach with sellers and buyers trying to optimize their own utility (profits, demands) or community utility (minimum aggregate cost or maximum social welfare in form of benefits) [7, 38, 69, 78].

Generally, agent based models can be N-type designs or autonomous-agent (AA) design [14]. With N-type designs, agents follow rules via linear or non-linear functions and have some adaptation strategy with herding or probabilistic switching mechanism. AA agents are associated with complex learning algorithms and thus sometimes new and improved trading rules are developed to define agents' behavior. N-type are based on predefined rules and qualitative models with laid out hypotheses.

The financial market models have three main components: Agent design, Agent learning and Price finding mechanisms (or Market Design) [49]. While the energy models have Agent designs/ strategies, Market design, Evaluation measures and outcomes as its components. The following sections discuss in depth the different components of the model designs which would help find the best-fit based on the laid out energy market issues in Section 1.1.

2.1. Review methodology

The keywords which were used in the literature research here were: Rural India AND/OR Developing Countries AND Renewable AND/OR solar energy, Energy Trading AND markets, Culture models AND markets OR Trading, Partner selection AND agent based modeling AND markets, Culture models AND markets, Energy Trading AND Developing Countries OR India, Kirman AND markets, Discrimination AND agent based modelling. The search engines and the repositories used for search include, but are not limited to Web of Science, Google Scholar, Scopus, ScienceDirect, ResearchGate and Elsevier.

The first aim was to find exhaustive literature reviews based on these keywords. If they were available and were comparatively new (2010 or ahead), then based on these literature reviews, in-depth analysis was done on related papers as per the defined research gaps. E.g. On searching the keywords "Partner Selection AND agent based modeling AND markets", an exhaustive literature review was found [49]. Based on the literature review, many papers were found related for this study and they were used here e.g. Kirman and Chen's Agent Based models [15, 39]. The next step was to look for the papers which have cited these relevant papers e.g. discrimination papers were not directly useful, but once looking into the papers which were cited here, helped in getting closer to the models' designs this research aimed at e.g. heterogenity in agents. The literature on renewable energy helped in understanding the context well and the issues faced in the Rural India and how relevant these solutions were for this specific case. This review was followed up from the previous research on policy analysis (research thesis by author at TU Delft) and extended for specific modeling issues.

2.2. Agent design and strategies

Looking into the agent designs, there are mostly Zero-intelligence(ZI) strategy based agents, where the agents are constrained (ZIC) e.g. by resource restrictions, or agents are motivated by profits (ZIP) [16, 23]. Most of the literatures on energy market agent based models define agents as ZI agents initially to understand the outcome of the market model given its rules.

A number of different strategies are available for agents for bidding and acceptance in computational market models [75]. They range as giving random bids, sniping (or last minute bids) and also frequency analysis heuristics learned strategies. The acceptance of a bid happens by comparing it with a given threshold, by comparing with the upcoming bid or simply based on number of iterations or times. The relations with agents are sometimes given more importance than personal utility, and this can be included in the strategies.

The intermittent and unsteady markets of energy generation and demands makes it necessary for operators to optimize their bidding strategies with considering new (evolving) constraints [81]. Even with a decentralized market, the market behaves like an oligopoly due to " limited number of suppliers, long construction periods of power plants and capital investment sizes, transmission constraints" [45]. Additional to the above mentioned strategies, the other biding strategies in the electricity markets can be detailed out further: (1) market pools where the mediator doesn't fight for the specific customers, but for the right to supply energy to grid (2) Bilateral contracts allow for the suppliers and buyers to chose their own terms and conditions for transaction. (3) Hybrid markets come with ancillary services (AS) e.g. frequency and voltage controls.

2.3. Agents learnings

Agent can learn via inductive learning as in the autonomous agents or they can learn by switching mechanism where they switch over time their type out of a set of two or more options corresponding to alternative strategies [49]. These switching mechanisms are further divided into probabilistic switching i.e. based on the social pressure of the majority [39] and evolutionary switching where agent changes its strategies depending on the relative performance. In probabilistic switching, the agents switch their behavior by randomly meeting another agent and adapting their strategy (with a given probability), or change their own opinion independently. It is achieved by agent comparing a measure of individual profit to average of all agents' profitability measures and sticking to current strategy by binary choice model [20]. The evolutionary switching is done by multinomial Logit probabilities from a discrete choice model or part of two-stage independent Bernoulli experiments with success-failure probabilities based on the peer pressure [8, 15]. In some models, the reinforcement learning is used for buyers' learnings and the maximization of profits that the buyer receives help the buyer to decide.

It should be noted that the agent based on learning are "homogeneous ex-ante, but heterogeneous ex-post" [14] i.e. they are similar in many properties initially, but due to the learnings, their properties change and they become different from each other (heterogeneous). This is also the case in this research because agents meet frequently in market (agents may not meet physically, but their demands are met with the available supply and vice versa which affects their future demands-supply). Basically, the agents can change their own choices, constraints, and behaviors due to their interaction with other agents [22].

Provided the limited past private information agents have, without any access to the public information, a comparative study of qualitative behaviors obtained from different choice functions is discussed in [53]. Here, the probability with which the buyer choses a seller is based on his knowledge of the stored information of the sellers. Note that the information is accumulated only during transaction and this information builds with time as

$$J_j(t) = \gamma J_j(t-1) + (1-\gamma)\pi_j(t) \tag{2.1}$$

where J_j represents the information concerning the jth seller and j ranges as per number of sellers and π_j is the actual profit from the jth seller and γ is less than 1 as events far in past are forgotten. This explains the trade-off of the buyer between the frequency of visits to every seller and immediate profit.

2.4. Market design

2.4.1. Financial trading

In financial trading, trading orders in traditional ABMs are batched together and executed at same price and time, like an auction model. The market equilibrium is decided here by a market impact function, where price change is function of aggregate excess demand [15, 47, 48]. The other way to clear excess demand is by Walrasian tâtonnement procedure where numerical analysis demands price where there is no excess demand and all agents trade at this price [2]. But in case of intraday ABM, a continous market is implemented where trading demand is disclosed asynchronously and the different orders are matched by limit order book at various prices.

2.4.2. Energy trading:

Additional to the financial market, there is some literature on the energy markets as well. The energy market designs focus on the matching algorithms for the buyers and sellers matching, and the following paragraphs discuss these different matching algorithms. Some of these literature give a comprehensive analysis of different studies which help in going in the depth of specific studies e.g. [53, 82] compares various different energy trading models.

In one of the studies on energy trading, a multileader-multifollower strategy was used, where sellers decide the price and the buyers are passive price takers (follow in making the unit price bid) i.e. they are acceptors or rejectors of this price [43]. Here, the buyers are allocated energy in proportion to the bid and the revenue is allocated to sellers in proportion to their sales. The buyers have utility based only on the price they get, while the sellers have utility based on the revenue and the energy available with them. The energy available, stored in the form of battery, decreases with time as a logarithmic function (law of diminishing returns). The local selling price is always less than the market selling price and the local buying price is always higher than the market buying price. Here, the leaders are able to maximize their utilities based on the best responses of the followers. The solution delivered here is called stackelberg equilibrium, and it is found with the best response of buyer, followed by fitting in the seller's utility and optimized.

Further strategies in electricity market are explained by Ott et al. [57]. Basically once the sellers and buyers (or just competitive sellers) have put their price-quantity bids and their bidding period ends, a mediator matches the offers from sellers with the bids from buyers and the bids of highest price are matched with offers of lowest price. After all the demands are met, the price which is set as the market clearing price (MCP) is the one which is usually the last accepted/ first rejected offer. Additionally there can be a uniform pricing, where all the suppliers who win (in the auction) gets paid at the same MCP, or they get paid-as bid (PAB) where they get paid at bidding price or committed amount of electricity [7]. There can be hourly bids or daily bids in a market. The bids are given by the suppliers and they are a tuple of the tariff cost and the amount of the electricity they are ready to sell. The buyers have a "merit" or "reputation" associated to them. The sellers are stacked from the lowest to the highest bid. Buyers are also lined up as per their merits or reputation. The reputation can be alloted as per their fairness, amount of demand, their non-cheating behavior, etc. Then the demands are filled in the order of the supply available one by one [7].

Few optimization approaches are laid out by Prodan et. al which focus on (1) the effects from other external grids with increasing the battery utilization of the battery during the high demands, and (2) utilization of more renewable energy resources with the aim to depend less on external grid and more on the renewable sources of local market [60]. This model takes into account the uncertainty and errors of prediction and tries to optimize the behaviors of the agents (sellers) reducing the prediction error to achieve better market efficiency. In [69], player determines bids in real-time as well as day-ahead. Here, the uncertainty of the bids of the players in markets, agents solve their self-scheduling problem to maximize profit. Due to the player's decision on both quantity and price, supply function equilibrium is used. The objective function are based on price limits and cost of production and revenue. In this supervisor (aggregator) collects producers' offers and consumers bids and maximize social welfare("the sum of net consumers' surplus and the suppliers' profit"), or minimize the total cost.

The neighborhood energy trading explicitly laid out by Ilic et al. with a "noble" market design approach (motivated from stock exchange market), and the market has public information of the best buy and the best sell always. The inclusion of zero-intelligence agents (at the start) and with access to its own future production and consumption behavior, new prices are generated based on the last rewards. This model shows that the market efficiency drops with supply meeting demand and increases with supply better than demand [38]. Matching of the buyer and sellers similar to the stock market on a first come first serve basis and thus timing of the bid plays an important role here. An order chart is made for bids by buyers and sellers and the order chart is available to the bidders. The top (lowest) sell and top(highest) buy in order chart sets range for the future bids and if $p_{buy} \geq p_{sell}$, then a transaction is done[38]. For design of the agents, A zero-intelligence agent is build without memory or profit-motives. It bids randomly between two price limits and has a 'sleep-time' when it waits for next bid.

The strategy-proof double auction method is discussed in one of the literatures that ensures "that no seller or buyer has an incentive to change or cheat about its true reservation bid or price [64]." This approach lays down an auctioneer or a mediator who publishes the prices and also informs the sellers of the opponents strategies. There is also a private method, where seller estimates its utility and submits a price based on information from the auctioneer.

Model by [80] discusses Continuous Double Auction (CDA) which allows agents to keep making offers continuously in the market until and improve upon them until a transaction is reached. This allows prices the flow of electricity and thus manages the congestion within the system. Certain mechanisms are discussed here to ensure the system should be able to cope with unforeseen demand or any increased supply capacity in real time.

A yet another literature by [42] implements a highly flexible market platform for coordinating self-interested energy agents, which includes power suppliers, customers and prosumers. The policies which govern the bidding strategies of these agents represent user constraints controlled by the agents. The solution here incentivize the agents to reveal their policies truthfully for efficient solution of the overall system. The model in [43, 78] uses a single-leader multiple-follower Stackelberg game. A central power station(CPS) interacts with number of energy consumers(ECs) and this is modeled. The CPS is leader here which tries to minimize the total cost of buying energy from ECs, and ECs maximize their utilities by deciding how much energy to sell. "It is shown that the game, which can be implemented distributedly, possesses a socially optimal solution, in which the benefits-sum to all consumers is maximized, as the total cost to the CPS is minimize."

2.5. Evaluation measures and outcomes

The evaluation measures in the agent based models are for two purposes: (1) To check whether the model is performing well as expected or not as the reality, and (2) To understand the new insights from the model or perform comparisons of different scenarios. For the first, one of the measures used in the literatures is to check the prices' responses to the demand and supply. Basically it checks that prices should decrease when supply is more than demand and should increase when demand is more than supply [38] To get further insights in the model, usually social welfare is checked which is "the sum of net consumers' surplus and the suppliers' profit [69]"". A measure of efficiency is also discussed in literature called as allocative efficiency, which is the "ratio of traded energy to the maximum amount of energy that could have been traded in a timeslot [38]".

Model by [7] shows the bilateral markets to have better effects in making markets more efficient than mediator involvement. Kirman further discusses in his literatures that loyalty of local buyers towards sellers, given as a weighted average of the past appearences, increases their utility, as the gross revenues from local buyers increase for the sellers [40]. The information asymmetry between the buyers play a large role in influencing the decision about the sellers. The individual and aggregate behavior of the market is not the same always e.g. the downward sloping demand curve only happens when all individuals are equally constrained by budget [25]. But at the same time the prices set in equilibrium in auction markets are function of quantities.

2.6. Culture Models

Culture affects immensely trade partner selection [29, 30]. Different literatures on Hofstede's five dimensions of culture are included in various models and the effect is studied on the partner selection for trades (in food supply chain market with small-scale firms). In these models, the information among the agents is asymmetric. The *partner models* helps in defining the agent's beliefs where agent's five labels of culture dimensions are public and all other information is private. These dimensions: *Experience based trust*, *group distance*, *Societal status*, and *expected utility* are stored in the partner model. The effect of the culture and the probabilities to accept partner is modeled in these literatures[31–36].

Some of the results show that in masculine society [1], the agents are less loyal, but the powerful agents quickly learn to exploit their power and it results in increased cross-class (i.e. inter-groups) shopping. Other results show the impact of the long term versus short term oriented agents [2]."Long term oriented agents accept high quality transactions, because they take their time to negotiate a price that covers the risk. The short term oriented are less patient and break off more frequently, but this effect is reduced when they trade

[1] "Masculinity is seen to be the trait which emphasizes ambition, acquisition of wealth, and differentiated gender roles"
[2] Long term oriented agents aim higher aggregate returns in future, while short term oriented look for quick profits in recent future

with high status partners." These results help in defining the evaluation parameters for the models.

2.7. Conclusion

The literature review is performed to answer the first research sub-question: "What are the issues with the existing solutions with respect to discrimination and efficiency in energy trading?" It is laid out in Chapter 1 that the focus of this thesis solutions is on the agent based models which help understand the conflicts and the discriminations in the market. The agent based models first need a definition of agents itself and looking at the literature as described in Section 2.2, the zero intelligence agents are chosen here. The agents are motivated by profits and decide their bidding strategies as per their profits and costs in the earlier rounds. Agents learn or take actions, as discussed in Section 2.3, based on the evolutionary switching mechanisms here, i.e. based on their own relative performances.

Coming to the market models, the market design is studied in literature for both financial markets and energy markets. Based out of all strategies, the strategy as laid out in [38] of ordering of bids is implemented. Here, as discussed in Section 2.4, an order chart is made as per the bids by the buyers and the sellers. The top (lowest) sell is matched with the top(highest) buy, and so on, and then transactions are done. The bid prices are randomly chosen in the given range and the bids are updated every round. Evaluation measures as discussed in Section 2.5 helps define efficiency, social welfare and other evaluation or performance measures for the model. Finally, the cultural models' literature laid out in Section 2.6 helps define the impacts on the partner selection and other functions of the model based on the cultural parameters. The choice of the methodology for the models and their design using inputs from the literature is discussed in Chapters 3-4.

3

Introduction to models

Based on the research questions and the literature review in the last chapter, this chapter discusses the choice of methodology as in Table 1.1. The definition of the models, experiments and the evaluation is also discussed in this chapter. The first section 3.1 discuss the design of the agent based models and why the agent based modeling is chosen for this thesis. This is followed by an explanation of the different types of models and mechanisms used to define the experiments laid out in Section 3.2. Section 3.2.2-3.2.4 lists the mechanism and finally, section 3.2.5 lays down the definition of different experiments based on these mechanisms. The evaluation measures are laid out in section 3.3 which describes the measures to compare different experiments. Section 3.4 lays down the hypotheses which will be checked in the thesis.

3.1. Agent based Models

For this thesis, simulation models are chosen to answer the second sub research question on "which cultural and market models fit best to understand and test different mechanisms to study the discrimination?" The simulation models are chosen to be agent based models here because they allow introducing agents who can interact in a market setting i.e. the environment of the model. Considering the context of the energy market governed by profit and different social types (castes) of people in market, ABM allows to model agent individually with different properties as well. Thus, ABM is chosen for this study. The interactions of the agents as transactions can be modeled well in ABM with agreements or bid matching based on the agreements of price and quantity of bids.

Here, the agents in the agent based models try to match their bids i.e. their prices and quantity of their sales and demands. In real markets, the bid matching happens either one-time or with repetitive negotiations

[9, 10, 18]. The one-time matching involves that the bids are matched once and even if there is no match, the market can close. In this case, the agent learns how to bid the next day market opens. The other way the markets' bid matching work is where the agents negotiate or change their bids till there is a match, and only then the market closes. The current thesis focuses on the former type of the market because the focus of thesis is on a rather small size of the market where agents do not have much freedom to change their bids. For example, majority of the agents have limited production to sale or decided consumption quantity. Also, the income constraints of agents do not allow them to negotiate beyond their affordability. Thus, the decisions in these agent based models are one-time events.

The agent based models allow transactions or interactions of the agents where two agents trade energy. This can happen bilaterally i.e. this can be a direct peer-to-peer exchange between the people who are selling and the people who are buying, which allows them to decide their own partners. These models can also be called as "bilateral" models. Bilateral models resemble the real world peer to peer energy sharing markets, usually in case of renewable energy sources. For example, a household can share its excess produced solar electricity to other household who is in higher demands than its own production limits. The peer to peer energy sharing can happen over grids or via simple exchange of batteries (stored energy sharing). The example of both types of systems exist in reality [1] and the former allows flexibility to share any quantum of energy but needs much bigger and better infrastructure system. The latter is more flexible in terms of the distances the energy can be shared. It is very difficult to make the seller and buyer anonymous as the physical exchange of goods (batteries) happen in the case of bilateral exchanges. Thus the effect of cultural influences is much stronger in the latter, which affects the partner selection for energy trading.

3.2. Mechanisms

The aim of the thesis is to understand how these cultural influences can be minimized to have a non-discriminatory type of partner selection. Thus, different automation and non-automation[2] mechanisms are introduced to reduce the discrimination. These mechanisms are discussed below in detail after explanation of the exact definition of discrimination.

3.2.1. Definition of discrimination

Before explaining the mechanisms, it is important to lay down how the models define the social discrimination in this case. There are two main definitions of discrimination - for the agents, and for the mediator. These definitions are explained below.

Discrimination among agents: The discrimination for agents is defined here in two forms (the first case is implemented in the final model):

[1] In the South-East Asian context of developing countries, some examples are Rural Spark (`www.ruralspark.com`) which allows sharing of energy using batteries and Solshare (`https://www.me-solshare.com/`) which facilitates sharing of solar energy using grid

[2] Automation mechanism simply means something which would not need a human interference in the real market

1. As a "social envy": First, based on the income value of the agent, the agent is decided to be poor or rich
   (a) All the values of the incomes are normalized [0, 1]
   (b) An equal distribution ("renormalization") for the population is developed in [0,1]
   (c) The renormalized values are subtracted from the normalized values to understand if the agents have a higher (positive) or lower (negative) income than expected in equal distribution. Then these values are reallocated to the respective agent.
   (d) If the above values are negative, then the agent is considered poor [3] and then if the trading agent (partner) is rich, the probability of rich agent for trading energy with the poor agent would be really low (20%). If an agent is poor, the probability of it trading energy with anyone would be 100%, while for the agents who are average have a probability of 60% to trade with poor agents.
2. Caste based: If the agent is from high/low caste, then the "biased" agent is not ready to trade with agent from the other (low/high) caste. The proportion of the agents who gets chosen at random with the "bias" as TRUE are much higher (90%) for higher caste than the lower caste (5%).

Discrimination among mediator Additional to the above discriminations, the mediator discriminated based on chance. For understanding the effect of such a discriminatory mediation, a "bias degree" variable is associated to every experiment. How this works can be explained with an example for the caste based discrimination. If this value is 0.4, there is 40% chance for the mediator to be "biased". This means that there is 40% chance that the mediator will be discriminatory and thus would not allow a partner from a lower caste to do transaction with higher caste or vice versa and only allow intra-caste transactions.

3.2.2. Mechanism: Mediated model

The other type of transaction that can happen instead of bilateral in a real market would be through a mediator or a central agent who collects the bids of the buyers and sellers and then allocates each of them their partners. This agent can be a human in real world e.g. a shopkeeper who collects all the charged up batteries together and then sells them as per the demands. The other form of this mediation can be through an automated tool/device in between the grid distribution. The following figure 3.1 shows how transactions are different for a bilateral and mediated transaction model.

3.2.3. Mechanism: Mediator discrimination

As discussed above, the mediator can be a human or a device based on the nature of the energy sharing in the real world. To reduce discrimination, ideally the mediator should be non-discriminatory itself. But, as there is chance of the mediator to be human, there are chances of him/her to be influenced by the cultural biases of favoring one caste (social type) member over another. In case, it is simply an automated mediator,

[3] A simpler way to check for poor or rich agent is that after step of normalization - The values higher than 0.67 are considered rich, while those below 0.33 can be considered poor, and those in 0.33-0.67 are average.

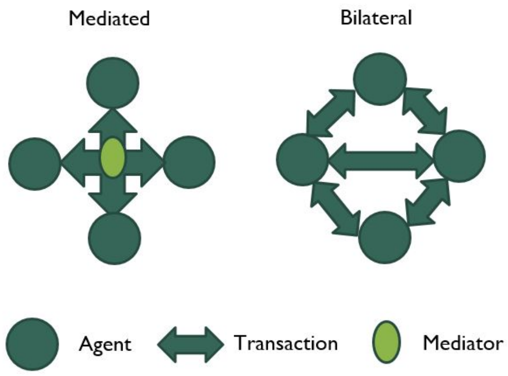


Figure 3.1: Bilateral versus mediated transaction models

the mediator would generally be non-discriminatory, unless tampered with. These cultural influences on the mediator again influence the bid matching and partner selection. Thus, a new type of mechanism in the model is introduced with discriminatory or non-discriminatory mediation, as depicted in Figure 3.2.

For understanding the effect of the such a discriminatory mediation, a *bias_degree* variable is associated to every experiment. How this works can be explained with an example. If this value is 0.4, there is 40% chance for the mediator to be "biased". This means that there is 40% chance that the mediator will be discriminatory and thus would not allow a partner from a lower caste to do transaction with higher caste or vice versa and only allow intra-caste transactions.

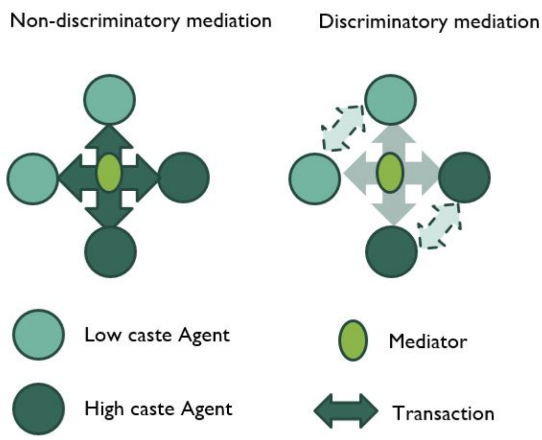


Figure 3.2: Discriminatory versus non-discriminatory mediation

3.2.4. Mechanism: Bid Split

The mechanisms can also be incorporated in the form of bidding and acceptance strategies which would allow to reduce discrimination and increase efficiency. One of such mechanisms used in this thesis is called "bid splitting" which involves dividing the quantity of the production of the seller and the consumption of the buyer in equal number of chunks. Each agent bid's are divided into chunks of constant number of watts.

Thus, large bids just constitute higher number of bids of same size/chunks compared to smaller bids. Usually, the size of production is associated to the richness and the social type of the agent. As the agents are matched now as per every chunk or small size of bids associated to agents, agents cannot use the bid size to infer the social type of the producer. Also, note that bid splitting is only possible in case of mediated model and not bilateral because in bilateral agents meet and their identity cannot be protected.

Taking an example, if a seller A bids 1.4 W and the buyer B bids 3.2 W, then the split bid would look like (1, 0.4) and (1, 1, 1, 0.2) divided over 2 and 4 rounds of bidding respectively (bid matching rounds would happen as per the length of the array of bid). In this case, even if the buyer A is poor, B cannot infer it from the way the bids would be presented to it for every round. Thus, there is high chance to prevent discrimination in bid split. Even in case of social envy based discrimination, as an agent cannot infer the income/produce of the allocated partner agent, the bid split helps to prevent discrimination.

There is an important point to note here for the size of the chunk of the bid splitting. On bid matching seller A would have updated bid of (0.4) as it would sell 1 W and buyer B would have updated bid of (1, 1, 0.2) as it would buy 1 W. It can be seen that the size of the chunk of bid plays a crucial role in bid-matching, because if the size would be 0.1 W per chunk, the seller A would have everything sold while seller B would have 1.8 W left. Another important note to bid split here is that even if the discrimination reduces, the rich agent (or the agent with a higher produce) can still sell more and thus still would get higher rewards. The bid split is allows the poor agents to have better access to market and not necessarily high rewards (as rewards are proportional to produce).

3.2.5. Mechanism experiments

Based on the above explained mechanisms, different sets of experiments are designed to test the different mechanisms to reduce the discrimination in energy trading.

1. **Base case:** Bilateral Partner selection with discriminated agents.
2. **Experiment 1:** Mediation partner selection without discrimination and without bid splitting
3. **Experiment 2:** Mediation partner selection without discrimination and with bid splitting
4. **Experiment 3:** Mediation partner selection with discrimination and without bid splitting
5. **Experiment 4:** Mediation partner selection with discrimination and with bid splitting

An important note here is that the model for mediated model looks very close to the auction models. This is so because in the mediated model, similar to the auction model, the bids are collected together and then bid matching is done. But unlike auction model, the mediated model doesn't have open auction i.e. the bids are collected anonymously by the mediator. The second important difference is that the bids here are not only made based on the tariff/ cost, but also the production/ consumption quantity. Thus, even with the similarity of the auction models with mediation, it has some major differences. The next chapter explain the design of the functions which clarify the difference from the auction model.

3.3. Evaluation measures

Once these experiments are conducted, the data gathered can be used for overall evaluation for the models (i.e. how do they perform). For the same, different evaluation measures are defined and calculated per experiment. This would be explained as per the different literatures considered for defining them, and the final definition and governing equations for each of the measures.

3.3.1. Seller-buyer inequality

The first measure "Seller-buyer inequality" checks for the inequality of the agents as per their decision to be a seller ($value = 2$) or a buyer ($value = 1$) or take no role in the market. The *values* for decision are given here for ease of calculation of the seller-buyer inequality value. Simply put, it is the inequality of distribution of decisions i.e. distribution of number of sellers and buyers. More is the unequal distribution, higher is the seller-buyer inequality value. Across literatures, seller-buyer inequality is defined as "half of the relative mean absolute difference, which is mathematically equivalent to the Lorenz curve definition" [44, 67]. If x_i is the value for agent i, and there are N agents, then the Seller-buyer inequality G is:

$$G = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}|x_i - x_j|}{2n\sum_{i=1}^{N}x_i} \tag{3.1}$$

3.3.2. Social welfare

Social welfare is defined differently across many economics literatures. The three main categories of social welfare definition are: Bergson–Samuelson [4, 65, 66], Arrow [1] and Cardinal social welfare. The first two definitions depend on the given set or different possible set of individual preferences for welfare. While the last one, cardinal social welfare, assumes that individual utilities can be compared or used to return the total community social welfare. As the community design in the agent based model here is kept simple, the agents do not have a preference for the welfare and thus, the cardinal social welfare would be preferred.

Among the different cardinal social welfare definitions, there are two important definitions: (1) utilitarian or Benthamite function [55], and (2) Rawlsian social welfare function [26]. There are some other definitions as well. e.g. by Sen(1973) using the average and the inequality of the incomes of the population [68], by Foster(1996) by using the average income and the income of a randomly chosen agent [21]. The first two definitions of Benthamite and Rawlsian function would be discussed here as the others are already combination of other measures or these two definitions. E.g. Sen's definition is combination of Benthamite and Seller-buyer inequality measure discussed in section 3.3.1.

Benthamite function gives social welfare as the sum of individual incomes of the agents. This can be expressed as Equation 3.2, where Y_i is the income of agent i for N number of agents. This definition is slightly adapted here for implementation purpose of the model. The *net* income of the agents in the models here is the difference of the rewards or the profits they make and the costs they incur. Thus, the social welfare is adapted as Equation 3.3, where R_i and C_i are rewards and costs of agent i.

The costs for the agents are usually a one time payment in this context of solar energy usage. These costs are paid off before the usage and can be considered as fixed costs. As everyone have to pay them they can be ignored. Also, there is a variable cost based on the maintenance of the devices (shops) used to produce(sell) energy. But these variable costs are very low and thus can be ignored as well, as defined in Equation 3.4.

The other definition of social welfare as the Rawlsian function is the minimum of the utilities/ income of all the agents, where income of the agent i is Y_i. For implementation, this definition is also adapted by replacing the incomes Y_i to rewards R_i of agents as shown in Equation 3.5. Thus, as per all the definitions, higher value of all social welfares are preferred. Out of the given two definitions: Benthamite (eq. 3.4) and Rawlsian (eq. 3.5), the second one is preferred for this specific context. It is so because in this context there is maximum discrimination towards the poorest of the community and thus increasing rewards for the poorest (those with lowest rewards) would be a good measure. The results in Chapter 6 would still be compared for the Benthamite function for total, and the social welfare of the lower and higher castes each.

$$S = \sum_{i=1}^{N} Y_i \tag{3.2}$$

$$S = \sum_{i=1}^{N} (R_i - C_i) \tag{3.3}$$

$$S = \sum_{i=1}^{N} R_i \tag{3.4}$$

$$S = min(R_1, R_2, ..., R_N) \tag{3.5}$$

3.3.3. Wealth inequality

Additional to the inequality of distribution of the decisions, it is important to evaluate the distribution of wealth among the agents to understand if everyone is getting the benefit of a mechanism or not. This is done by introducing "wealth inequality" measure which is basically the *seller-buyer inequality* for the rewards or the profits of the agents. Lower is the value of this measure, higher is the equality of the wealth inequality. The definition of wealth inequality is obtained from the seller-buyer inequality coefficient because originally the seller-buyer inequality coefficients were used in literature for measuring income inequalities in countries [**? ?**].

There have been discussions to measure the inequality of opportunity i.e. seller-buyer inequality for social development in a different way [63, 67] e.g. while taking the decision to be a buyer or a seller, the previous background/ privileges of an individual should be included. But for simplicity and uniformity of definitions with *Seller-buyer inequality* in Section 3.3.1, these will not be considered here. The equation for wealth inequality would thus be as in Equation 3.6. The wealth inequality is obtained and compared for lower castes and higher castes (different social types) as well.

$$W = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} |R_i - R_j|}{2n \sum_{i=1}^{N} R_i} \tag{3.6}$$

3.3.4. Market access

The evaluation measure of *market access* checks for the proportion of the number of agents who got partners compared to those who needed partners. This specific definition is chosen here to understand the efficiency of the complete market i.e. how well the bid matching allows in different experiments to actually allocate a partner to a given population. Market access in literatures [3, 27] and across industries [4] is usually used at a larger scale where countries are involved in trading. The amount of goods actually imported-exported and the costs which are developed as "trading tariffs" in these trades, help in calculating this market access.

Bringing such values to a very low scale of small communities trading only one type of good (here, energy), the definition of market access translates to the actual transactions (imports-exports) that happen in the market. As the tariffs of the agents are not updated during the trade in this study, as was discussed in Section 3.1, the "tariffs" of the agents would not play a significant role in deciding market access here. It should be noted though that the tariffs play role initially while matching of bids, or basically making the transactions possible. Market access is also calculated in total, and individually for higher and lower caste. For ease of implementation, this definition is adapted to proportion of agents who are able to do transaction (find a partner) as in Equation 3.7, where P_i is the partner for agent i. It can be seen that the higher market access would be preferred.

$$M = \frac{\sum A_i}{N} \begin{cases} A_i = 0 & \text{if } P_i = \text{None} \\ A_i = 1 & \text{otherwise} \end{cases} \tag{3.7}$$

3.3.5. Efficiency

The evaluation measures till now check for the total social good, but it is also important to understand how each individual is benefiting from a given mechanism or experiment. Thus, the final measure of *efficiency* is introduced here. It is defined as the average ratio of traded energy by an agent to the maximum amount of energy that was available to be traded by each agent. Efficiency is defined across multiple fields of engineering and economics, but here the definition of operational efficiency will be considered as it allows measuring the efficiency of each transactions. An operational efficient market is when the profits are highest with lowest fees. In case of the constant fees this translates to maximum goods sold in short time [24]. Thus, efficiency is described as in Equation 3.8 below, where S_i is the actual quantity of energy transacted and K_i is the quantity

[4] `http://www.macmap.org/SupportMaterials/Methodology.aspx`

of energy available for transaction for the agent i.

$$E = \frac{\sum_{i=1}^{N} \frac{S_i}{K_i}}{N} \tag{3.8}$$

Based on all these measures discussed the final sub-research question "How do different models perform for the measures of efficiency and discrimination?" can be divided into multiple research questions, e.g.:

1. How bid splitting will affect market access of poor sellers and buyers compared to non bid splitting?
2. How discriminatory mediation would affect social welfare compared to bilateral transaction?
3. How mediated models would affect wealth inequality as compared to bilateral models?

3.4. Hypotheses

All the mechanisms listed in Section 3.2 will be checked against the evaluation measures discussed in Section 3.3, based on the hypotheses which are made for the performance of these mechanisms. For each evaluation measure, these hypotheses are discussed.

Seller-buyer inequality: Mediated negotiation without discrimination and with bid split would increase the number of sellers in the market due to reduction of discrimination. This will lead to lowest seller-buyer inequality for the experiment 2. Thus, the highest seller-buyer inequality would be for the bilateral or discriminatory non bid-split i.e. base case or experiment 3.

Social Welfare: Mediated model with bid split would have higher social welfare than Bilateral model. Mediated allows better profits as there is no cultural bias when the mediator is non-discriminatory. Bid split also allows more agents to put their bids due to same size of divided bids. This allows even a poor agent or a low caste agent with low produce to have some rewards rather than none. Thus, this improves the social welfare especially for lower castes the most with non-discriminatory bid splitting mediation.

Wealth inequality: With the same logic of inequality of decisions an in case of *Seller-buyer inequality* and added logic of rewards as for *social welfare*, the inequality of distribution of rewards also hold. Thus, the value would be highest for base case or experiment 3 and lowest for experiment 2. The differences would be much higher within these experiments for lower castes.

Market access: Mediated transaction would have better market access for the poor than the bilateral transactions. In other words, more poor people will be satisfied with mediated transactions. Bid split reduces discrimination as well due to more equal bids available in market providing equal access to majority of agent. Thus every agent is equally accessible (not just those with the agents prefer) for a seller for a better match.

Thus, social welfare for both castes (but especially for lower castes) would be best for experiment 2 and worst for experiment 3 or base case.

Efficiency: Mediated allows better demand matching as demands and supplies of all agents are put together and then matched rather than one-on-one matching where agents might meet a non-satisfactory partner and leave the market sooner. Bid splitting allows a better efficiency with small size of chunks of bids as explained in Section 3.3.5. With large size of the bids, the efficiency goes even below the bilateral mediation in some cases. The role of discrimination usually plays a strong role in efficiency as many bids are unmatched due to discrimination. Thus, non discriminatory bid split mediation would have highest efficiency, but it will highly dependent on the bid split chunk size.

Comparison among evaluations: The bid split allows higher market access, but not necessarily very high rewards for the lower caste. Thus even if the market access for lower caste would increase a lot, the social welfare might not be very high for the lower castes. Similarly, the seller-buyer inequality would lower more as compared to the wealth inequality as well.

Comparison among mechanisms: The discrimination of the model is expected to be affected by the mediation, but the effects of bid split is expected to be much higher. This might be especially true for the market access (than the social welfare), as discussed above. Also, the effects of the bid split on evaluation measures would be higher as compared to the effects of simply reducing discrimination. This would be so because the bid split not only eliminates discrimination but also enables further market access to the agents from lower caste.

3.5. Conclusion

This chapter as followed from the last chapter on literature review, tries to define the choices used in the design of the model. First, it is concluded that the agent based models will be used in this study because these simulations would help model the context of energy trading market with cultural influences easily. Next, some mechanisms are introduce which would try to minimize the cultural influence which leads to discrimination in energy trading. These mechanisms involve introducing mediation in the bilateral energy trading in form of a mediator. This mediator can be automated or human agent and thus can be discriminatory or non-discriminatory i.e. influences by the cultural discrimination norms of the community.

The final mechanism of the bid-split helps in introducing splitting of the bids in small equal chunks such that there is no possibility to differentiate between a producer with high or very low produce. Four different experiments additional to the bilateral model are listed based on these experiments. All of these experiments are evaluated across different measures: Seller-buyer inequality, Social welfare, Welath distribution, Market access and efficiency. How different experiments will perform across these measures is put as different hypothesis which will be finally tested in the models as designed in the following Chapter 4.

4

Design

Based on the literature in Chapter 2 and the methodology in Chapter 3, this Chapter lays out the design for the simulation models, and the next chapter discusses the implementation. This chapter explains each function used in models for different experiments as in Section 4.1. All functions are designed such that the outputs of one can be used for input of another and this is arranged differently for different types of models and experiments as in Section 4.2.1. As discussed in further details in next chapter, the agent and its environment (supervisor) is implemented separately, and their designs are explained in section 4.2.2. This chapter defines the classes and functions for the model, based on the literature and model choices in Section 4.2.3. The final effects of the cultural models on the design of the functions here is discussed in Section 4.3. The design of each function in depth with the UML (Unified Modeling Language) diagrams are shown in Figures A.1-A.5 generated using plantUML.

4.1. Design of functions

Every function used in the models is defined separately with its inputs, outputs, side effects, governing equations in the following sections. The literature which helped defining these functions and their supporting pseudo codes will be explained in the next section 4.2.3. Other functions which are also used in the models are explained in Appendix A.

4.1.1. Perception

Components: `Perception` function's purpose is to store the values associated to an agent and they are broadly divided as `production`, `consumption`, `tariff`, `social type` and `biased`. The `production` and consumption give the value of how much the agent can produce and want to consume, respectively. The tariff gives the rate at which the agent wants to sell/buy the energy. The social_type is the agent's group, and for simplicity it is kept as low or high (caste). The biased parameter gives whether the agent is ready to trade with other social_type or not. For the biased value of 1, the agent is biased, and thus do not want to trade with other groups, while for biased = 0, the agents are ready to trade with anyone.

Initialization and updating: The perception dictionary associated to every agent is updated with the changing state of the supervisor and agents. This updating happens when the agents decides based on the decision function to sell or buy energy and thus the production or consumption is updated. This function gets its initial zero/None values with the components, followed by the measurements from a predefined distribution as defined by a MeasurementGen class, explained briefly in Listing A.3. The inputs of the function are the current measurements, obtained from the measurement generation function. There is no output of this function except for updating the state of each agent according to the corresponding input.

Agent-environment interaction: There are different possibilities how the agents can receive information from supervisor [1], e.g. either agent can recieve no information from the supervisor, or agents can receive partial information e.g. only of the environment from the supervisor. Also, agents can receive assymetric information due to bribery/ cheating of the mediator (i.e. some agents receive more information than others) or agents can receive all information about other agents from the supervisor. In this case, for simplicity and considering the small size of the community in the context, all the information stored in the perception dictionary of an agent is passed on to the other agents.

Bilateral versus mediated: In case of both bilateral and mediated model, the first update of the perceptions is the same, where get_measurements() collects the measurements and update parameters of the agents and the perception dictionary of the supervisor as seen in Figures 4.1-4.2. The difference in models with respect to this function is that the perception function in bilateral model also updates the state of each agent, which it doesn't do in case of mediated model till the decision function is called.

4.1.2. Partner Selection

Components: The function of partner_selection is used to obtain partner for an agent for trading energy. The selection of partner here is based on ordering bid where the sellers and buyers bids are ordered as per their tariff rates. The lowest bid from seller matches with highest of buyer and so on. For experimentation of bid splitting, the partner_selection is redefined where the production and consumption values of the agents are split into chunks and the same ordering of bids (as per their tariffs) mechanism is followed again. The governing equations and the pseudo-code behind these partner selections is shown for one of the case of mediated with bid split as in Listing 4.1 and the other cases are shown in Listing A.1-A.2.

[1] Supervisor is the environment of model defined as a different class and how this is implemented will be explained in the next chapter

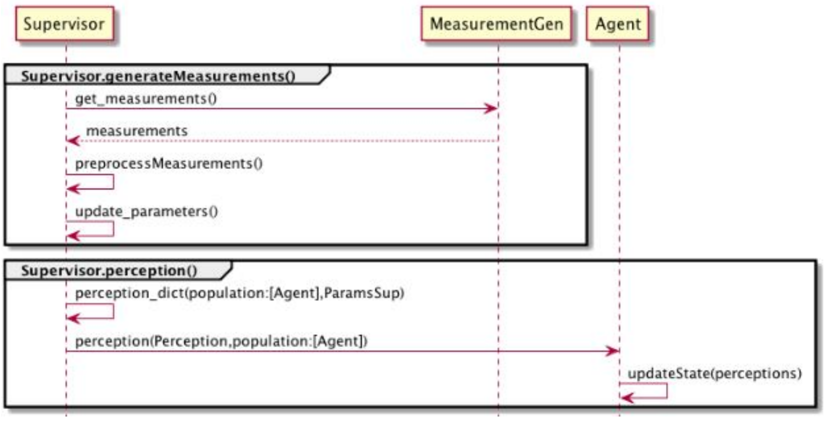


Figure 4.1: Perception protocol in Bilateral model

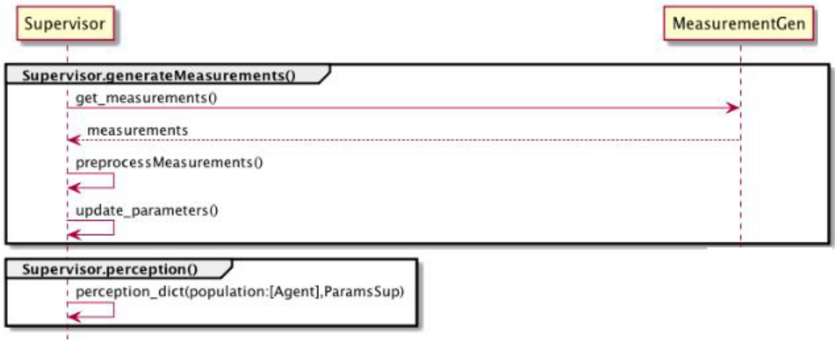


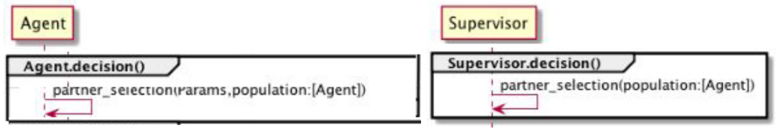
Figure 4.2: Perception protocol in Mediated model

Initialization and updating: In case of both bilateral and mediated models, the agent's own measurements obtained from the perceptions and the measurements of all the other agents (given in order as per the tariff rates) are the inputs which help in deciding the partner for the agent. The output of this function is the partner allocated for every agent in case of mediated model and partner allocated to the specific agent for the bilateral model. The `partner_selection` function leads to update of the partner from "None" to the partner, in case the agent is able to find a partner. Agents meet every seller one by one as the order of tariff. Also, they have a greedy approach i.e. as soon as it gets someone with comparable tariff and enough energy to sell or buy, the agent choses them as their partner. Familiarity of the player might also help here to make decision, but it is not considered for simplicity of the model.

Bilateral versus mediated: In case of bilateral model, the `partner_selection` is done by the agent itself, while in the mediated model, the `partner_selection` is done by the supervisor. In the latter, the supervisor collects all bids together, orders them and then allocates partner as per the production and consumption. In case of bid split, the agents get to match the demands with the selected partner till all the chunks of the bids are met, and thus the number of rounds are higher in bid split experiments.

Listing 4.1: Partner Selection Mediated with bid split

```
for agent in set of agents:
Allocate the "seller" or "buyer" status to the agent
Calculate the costs for the agent
if agent has "seller" status:
Add it to the list of sellers
else:
Add it to the list of buyers
Sort sellers with ascending order for tariffs
Sort buyers with descending order for tariffs
Divide the consumption of each buyer and production of each seller into equal chunks
Calculate "r" as minimum of length of sellers and buyers
while True:
if seller<r and buyer<r and r>=1:
        k = seller production - buyer consumption
        if k=0:
                if production of seller matches consumption of buyer
                        Allocate partner
                else
                        go to next agent
                Update seller production and buyers consumption to 0
        if k>0:
                if production of seller matches consumption of buyer
                        Allocate partner
                else
                        go to next agent in buyers
                if seller sells everything:
                        go to next agent
                Update buyers old consumption to transacted consumption
                Update seller production to difference of current production -
                and met consumption
                Update seller production in the sellers list to difference of -
                chunks sold till the last chunk is left
        if k <0:
                repeat the above process of k>0 for seller and buyer swaped
Return list of allocated partners to each agent
```



(a) Bilateral model (b) Mediated model

Figure 4.3: Partner selection protocol

4.1.3. Decision

Components: Decision function associates decision of buy or sell for every agent based on their partner and measurements. The decision function has two main components: `actions` and `costs`. The `action` is of selling (buying) which an agent can take based on if it has enough(excess) of energy to sell(buy) given its own consumption(production). For ease of implementation, the selling action is the given the value of 2, while the buying is given the value of 1. The `costs` are the maintenance costs which are associated to the seller, while the fixed costs are not included here as explained in section 3.3.2. The pseudo code for the function is provided below (with discrimination effect as explained in Section 3.2.1).

```
for every agent if there is partner:
r=richness of agent
p=production of the partner
based on r, p, allocate a probability of discrimination by agent
if agent is buyer and the partner is seller:
        if agent consumption < (partner production − partner consumption):
                allocate action buy to agent
                allocate action sell to partner
                partner production = partner production − partner consumption − agent consumption
                agent consumption = 0
        else:
                partner production = 0
                agent consumption = agent consumption − (partner production − partner consumption)
elif agent is seller and partner is buyer:
        if partner consumption <= (agent production − agent consumption)
                allocate action sell to agent
                allocate action buy to partner
                agent production = agent production − agent consumption − partner consumption
                partner consumption = 0
        else:
                agent production = 0
                partner consumption = partner consumption− (agent production − agent consumption)
return agent action
```

Initialization and updating: The initialization of decision function starts with giving zero/None values to the action and cost, while taking partner value from the `partner_selection` function. The perceptions value are also passed to the agent. The output of the function is the action that each agent takes and agents update their actions and costs based on this function. Either agents decide based on number of rounds, i.e. with iterations, agents decide one-off i.e. in one shot, or agents can decide based on past information or memory and here would give back the information to `Feedback`. In both the models, the first decision is made based on number of rounds of iterations (especially important for bid split), and then the final decision is used to update the rewards of the agent. This final step helps taking decision for the agent in the following rounds.

Agent-environment interaction: For both bilateral and mediated model, the decision is taken by the agent based on the allocated partner. The message of the decision may or may not be transfered to the supervisor. The total feedback and evaluation of the performance of the model needs information on decisions of all agents. Thus, the message of agent's decision is given to the supervisor (environment) as well.

Bilateral versus mediated: The decision to buy or sell is highly based on the biases of the agents in case of bilateral model or the mediator in case of a mediated model. Agents can opt out because they switch to a company/ central grid, or agents can use it for leisure (energy wasted): this simply means that agents would not participate in that specific round. But once the agent has put a bid in the market, they cannot opt out in this case till the next time-step. Agents can decide only to sell a part of their production, but here the production passed in the perception is already considered to be the part of the bid on the market. Agents can have stored preferences of its own, but it would need information from other agents already: through the `perception` function. In case of a mediated model, the decisions are only taken by the mediator and there is no possibility for the agents to deny the allocated partner as in Figure 4.4. In case of bilateral models, the decisions are taken by the agents themselves and the decisions are communicated to supervisor for storing it as in Figure 4.5. In case of bilateral model, agents will always receive information about other agents.

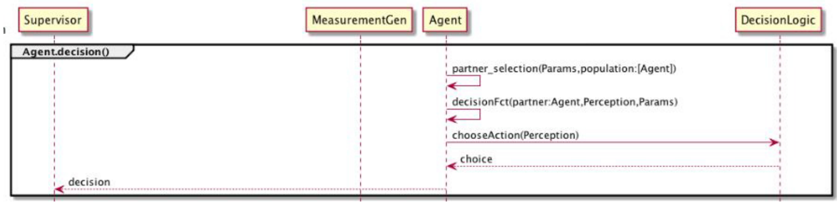


Figure 4.4: Decision protocol for bilateral model

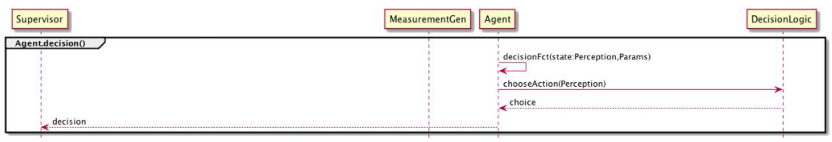


Figure 4.5: Decision protocol for mediated model

4.1.4. Feedback

Components: Feedback calculates overall reward for every agent based on their decisions and thus has the main component of `reward`. The `costs` are used to update the rewards while considering the next decisions agent's make for buying or selling. The pseudo code for the function is provided below.

Initialization and updating: The function is initialized with zero/None rewards for every agent and getting the decisions of each agent. The output is the reward allocated for every agent. The function thus updates the state of the agents i.e. the rewards help agent take decisions in following rounds. Agent learns about how well it performed to help take the decision in next round.

Agent-environment interaction: Feedback always comes from the supervisor, and it is given individually for every agent. In reality, the feedback can also go to the group/ caste leaders of the community or the feedbacks can also be biased due to discrimination (or other means e.g. bribery). But such cases are not considered here, for the simplicity of the feedback function. The feedback function is same for the bilateral and mediated model as shown in Figure 4.6

```
for every agent if there is a partner:
        if the agent is seller:
                Calculate transaction as difference of old production -
                and partner old consumption
                Update reward as the product of transaction and fixed profit rate
```

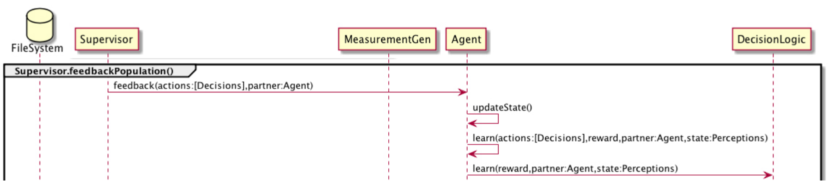


Figure 4.6: Feedback protocol for bilateral and mediated model

4.1.5. Evaluate

Components: Evaluate function computes measures based on agents information like social welfare, efficiency, seller-buyer inequality etc. discussed previously in section 3.3. These measures help understand the difference in performance of different models and experiments. The pseudo code for this function of evaluation is provided on the next page.

Initialization and updating: The function is initialized with setting all the measures value to zero, while the agents' perceptions, rewards and decisions are passed to the function. The output of this function is the value of all the measures and it also updates the state of the supervisor with these evaluation measures.

Bilateral versus mediated: The only difference between the bilateral and mediated model is that the evaluation calls the list of the rewards and decisions directly from the supervisor for mediated model. For the bilateral model, the list is made inside the evaluation function by calling each agent's decision and reward value. The common protocol for the evaluation function is shown in Figure 4.7.

```
Get actions, rewards, costs for all, high and low caste agents
Get agent−partner sets
Get the total number of agents who got partners
Calculate efficiency for every agent based on how much of the amount of transaction
Based on all evaluation measures, return every evaluation measure value
```

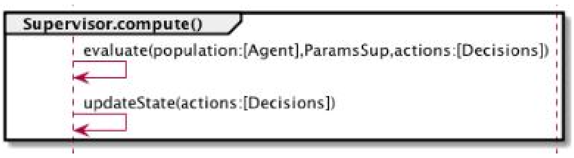


Figure 4.7: Evaluation protocol for bilateral and mediated model

4.2. Design of models

Additional to the design of the functions, it is important to understand the design of the models with respect to the agent and the environment design and the interaction of functions, as explained in Section 4.2.1-4.2.2. All the designs of the functions and model is derived from the literature and this will be also explained in the following section 4.2.3.

4.2.1. Modeling environment

For modeling the agent and environment, UML diagrams are used to lay out their designs in form of class and sequence diagrams, which are explained below and shown in figures A.1-A.5.

Class designs: Both mediated and bilateral models have two major classes: Supervisor class and Agent class. The Supervisor class holds the information of all agents in case of mediated model except for decisions, and in case of bilateral model holds the limited information of all rewards of the agents. This resembles a real world scenario of a rural community setting with bilateral or mediated energy exchange where supervisor actually takes role of the environment (community) or the mediator and environment, respectively. The other classes in the models are `MeasurementGen`, `DecisionLogic`, `RewardLogic`, and `EvaluationLogic`. For a bilateral model, there is an added class of the `DecisionLogicAgent`.

These classes have further functions like `get_measurements()` in the `MeasurementGen` which collects the measurements distribution profile to allocate to each agent. Similarly, `get_decision()` in the `DecisionLogic` helps allocate the decision (action) for every agent as discussed in the section 4.1.3. The `DecisionLogicAgent` calls this `get_decision` function to obtain action of every agent separately for each agent. The `MeasurementGen`, `DecisionLogic` and `RewardLogic` are varied further based on the variations in the functions implemented. E.g. the `MeasurementGenReal` uses the real data for generation of measurements to allocate to perceptions of the agents, while `MeasurementGenBinomial` generates binomial distributions for allocation to perception values of agents. These are further described in Appendix A.3.

Sequence designs: Sequence diagrams explain how different functions pass their information for working of the complete model. For the bilateral and mediated models, first the `get_measurements()` function generates the measurements which are given to the supervisor. `Perception` sends the information from the supervisor to the agent in case of a bilateral model. In case of mediated model, the perceptions just update the `perceptions_dict` of the supervisor. This is followed by partner selection by the agent based on the perceptions of the agent for a bilateral model. The partner selection is done in case of mediated model by the supervisor as only supervisor has the information of perceptions of all the agents.

`DecisionFct` associated to the class `DecisionLogic` or `DecisionLogicAgent` based on the mediated or bilateral model, gives a decision whether the partner is selected or not. The choice of the partner is passed to the agent from one of these classes. Once decision is taken by the supervisor (in case of mediated) or the agent themselves (in case of bilateral), they communicate the information to the agents with `Feedback` and calculate the rewards of the agents, and send this further to the `Evaluate` function. Generally, the process of updating in mediated models is: first supervisor updates state, gives information to all agents (or with preference to some agents) and then agents update their own state. `Evaluate` is where that once the decisions are taken, it is important for supervisors to evaluate final public good and this is done with evaluate by understanding the social welfare, etc. Finally, the decisions, rewards and evaluation results are all recorded with the `log`.

4.2.2. Modeling agents

There are multiple parameters associated to agent alone, and they are their perceptions, their decisions, their rewards and their costs. The decisions and the calculation of `actions` are already discussed in above sections in depth.

Bids: The components of perceptions are also discussed, but the main parts of the `perceptions` which comprise of the bids will be discussed here. These components are: production, consumption and tariff. All these values are given from real data distribution as discussed in Section 5.3. These values are passed specifically while partner selection and decision function are executed. The production and consumption values help compare different bids to allocate the sellers to buyers and vice versa, while the tariff rates help order the bids to allocate partner one by one.

Rewards: The rewards are partially discussed in the `Feedback` function description. They are calculated for each agent by simply multiplying the tariff rate of the agent with the production V_i transacted by seller or as expressed in the following equation 4.1 for every agent i, with tariff T_i. In reality, the buyer does get indirect rewards but this happens only after many rounds, and thus they are neglected compared to buyers.

$$R_i = T_i * V_i \tag{4.1}$$

Costs: Agent learn or get feedback not just based on the rewards, but the updated rewards with the costs which they incur for making the produce. The cost is usually divided into two components: variable and fixed cost. The fixed cost is neglected here as described in above section on social welfare. But the maintenance cost is used to update the rewards, though the effect is minimal. The following equation **??** shows the cost for every agent i where the cost is product of the constant maintenance cost M and the energy produced V_i.

$$C_i = M * V_i \tag{4.2}$$

4.2.3. Literature translation to design

To lay out the necessary functions, literature would be used in the models and this is briefly shown in table 4.1. The table depicts that which literature sections additional to cultural models are used to develop the functions. For example, the literature on Indian context helps define the measurements of the energy usage patterns and the social affiliations of the agents leading to the `Perception` function. The learning mechanisms' literature helps define how the agents learn and based on the new learnings, perform `partner_selection`. Other parameters like experiment settings are also inspired from literature as shown below in the Table 4.1.

Table 4.1: Defining functions from Literature

<table>
<tr><th>Literature section</th><th>Function</th><th>Other parameters</th></tr>
<tr><td>Trading dynamics in India [context]</td><td>Perceptions</td><td>social types</td></tr>
<tr><td>Agents design and strategies</td><td>Perceptions</td><td></td></tr>
<tr><td>Agents learning</td><td>Feedback, Partner selection</td><td></td></tr>
<tr><td>Market design in financial trading</td><td>Decision:Mediated</td><td rowspan="2">Environment</td></tr>
<tr><td>Market design in energy trading</td><td>Decision:Bilateral and mediated</td></tr>
<tr><td>Evaluate measures and outcomes</td><td>Evaluate</td><td>Hypothesis and experiments</td></tr>
</table>

4.3. Effects of cultural model on functions

As discussed in section 2.6, there are effects of the culture on the model here. These effects are modeled with understanding the exact impact on the functions. `Perceptions` and `partner_selection` functions are only functions to have cultural effects and there are no other effects of cultural model on any other functions, as explained below. It is also explained what different cultural effects are possible on the models.

4.3.1. Perception

The perceptions function helps passing the measurements of the agents and thus stores these measurements. The measurements can be influenced by status or the caste e.g. the consumption and production values are influenced by the status of agents. This means a new measurement would be added to the perception additional to production, consumption and tariff i.e. a social type. Here there will be only `social_type` or castes: high and low (based on modeling assumption).

4.3.2. Partner Selection

The partner selection would have highest effect of cultural model in case of bilateral transactions because the agents meet in the market. Thus, whom they chose as a partner gets affected here based on the culture. Here, there will be allocation of a "bias" measure which allocates a value of 1 for a biased (agents who only do transaction with their own caste) agent. These biased agents are randomly selected agents as per the given value of proportion of biased agents in a given `social_type`. For sensitivity analysis as in Chapter 6, this proportion will be varied and will be checked against the market access measure. As the discrimination is incorporated in this function, the effects of partner selection are the most important to study effects of mechanisms in the model. Thus, the validation will focus on the results' impact from this function.

4.3.3. Decision

The bids are given in decisions but these bids get affected by the partner selection and thus there is a trickle-down effect here. But, there can be a direct effect where the agent can decide to change its bid based on the partner (if the partner is not of its own preference) as well. The form of mediation can also affect here. If this is a auction form of mediation, where everybody can see the bidding lists, then the effect might be much more prominent rather than where the bidding lists cannot be seen (where mediator makes decision alone).

Based on how the model is designed, the cultural model would be included in decision function for bilateral model as simply an effect from partner selection. If the agent is biased (only choses partner of its own caste), and it does not get allocated a partner from its own caste, then the agent decided not to buy or sell based on whether it is a buyer or a seller, respectively. In case of mediated model, if the mediator is discriminatory, then it only allows for intra-caste transactions and prohibits inter-caste transactions.

4.3.4. Feedback

Feedback gives the overall rewards based on the partner selection and the decision of the agent. Here no effect would be assumed because in real world, once the agent takes decision the biases of the agents or the effect of biases from mediator ends. There will be a trickle-down effects due to the partner selection and decision biases, but no direct effect of the agents is used to allocate the lower rewards to the agents it does not prefer to be partnered with.

4.3.5. Evaluate

There are different measures of evaluation and each one of them can be affected as follows from the cultural model. But as all these are very objective function, the effect from cultural model will not be assumed. The possible effects are that the for the Social Welfare (amount of benefits of all agents combined), there might be an effect here because this helps define the utility of the agents e.g. the agents might have higher utility for trading only with the partner from the same caste. But in reality, the real benefit measure for a person is only monetary (profit) governed and thus, the cultural model is not considered. Another effect can be on the wealth inequality (distribution of profits of agents), but as these are by definition global parameter and objective, so they would not be affected as well.

4.4. Conclusion

This chapter starts with laying out the design of every major function which is used in the models: Perception, Partner selection, Decision, Feedback and Evaluate. The different aspects of these functions i.e. the components, the initialization, the updates of the agents and the environment based on these functions, and the interaction of the agent and the environment are discussed. The difference between bilateral and mediated models for these functions reveal that in mediated model, the update is first done in supervisor's state and then passed to the agents, except for the decisions. The modeling of the environmentis achieved by going into depth of the class and sequence UML designs and differentiating how information from one function is passed to another. All these designs are based on the literature and it is explained how different parts of the model design is facilitated with literature analysis from previous chapters. The final section explains the effect of cultural model on each of the main function in detail, and these designed functions will be implemented in the model as explained in the following Chapter 5.

5

Implementation

As per the design laid out in previous chapter 4, the next step is to implement this design in two main stages. Section 5.1 is the first step to develop a working model. The next steps are described in Section 5.2 and Section 5.3 which focuses on making the model closer to the real world scenario. It discusses that how the real world data is selected/ generated and plugged into the models for the perceptions of the agents.

5.1. Basic implementation

For the first step, Section 5.1.1 lays down the tools and the model framework used for implementation. The steps in which the implementation is carried out is listed in Section 5.1.2. The different experimental settings of the model for implementation of each experiment are also discussed here in section 5.1.3.

5.1.1. Model framework

The tool used in the thesis for making the implementation possible is Python MESA [1] framework. Python MESA helps to develop agent based models and the crucial parts of this framework is discussed here. The two most important components of MESA are: `Model` and `Agent` generic classes. The `Model` class contains all the model attributes, global level of the model and manages agents. This class here is called `Supervisor` class, which basically generates the general environment of the model.

Each instantiation of the `Supervisor` leads to a model run, and it will contain multiple agents which are instantiations of the `Agent` class. Each agent will have number of variables associated to it, but most important would be the `unique_id` or a unique identifier value associated to agents which distinguish them

[1] `http://mesa.readthedocs.io/en/latest/index.html`

from each other. The next important component of MESA is the `scheduler`, which controls the order in which agent gets activated. Activation here means that the agents take their own step. The step of an agent usually goes with the step of the model i.e the time advancement of the model. In models here, the simplest type of activation is used - `RandomActivation` - which activates all agents once per step in random order. Every agent has a `step` method where it takes the model object as its argument and executes agent's action as it gets activated. By creating a model object, e.g. giving the number of agents `N`, the model is run.

5.1.2. Implementation steps

Before implementing the final running models, various steps are done to make sure that the models are performing as expected. The first step is to create the skeleton code where as the sequence diagrams as in 4.2.1, the functions transfer their information. Further tests by passing different values through the `MeasurementGen` helps check that every class is implemented as expected. Then, each function e.g. the `get_decision` inside the `DecisionLogic` class is implemented by detailing the logic of the functions as explained in Section 4.1.

The real data is fed in the `MeasurementGenReal` class and the `perception` values for agents are updated. The outputs are generated for each experiment by varying the `partner_selection` in case of bid splitting experiments. The `get_decision` function is varied for differentiating between the discriminatory and non-discriminatory mediator. The outputs which are usually the results of the evaluations are stored in `log` for further data analysis or generating plots. The data analysis is finally followed with sensitivity analysis and validation, to check if the implementation of model is robust and valid for the given context, respectively.

One of the most important step here is to check if the model is performing close to the real world expectations (and assumptions). For the same, test models for checking the performance of different functions are written. One of the examples is shown below, where it is checked that whether the agents are being correctly allocated to the agents based on their individual measurement values. Similar tests are performed to check the right allocation of the rewards, the costs, and the partners to the agents to every agent. These tests are also checked for the performance of the model with evaluation measures. This is done by passing specific values, e.g. rewards are set to zero and then it is checked if the social welfare is zero or negative.

Listing 5.1: Test that the decision is updated correctly

```
def test_decision(self):
        self.a.decision_fct=DecisionLogicTestingDynamic(self.a)
        n=np.random.randint(1,20)
        perc={i:"a" for i in range(n)}
        dec=self.a.decisions(perc)
        self.assertEqual(len(perc),dec)
```

5.1.3. Experiment implementation

In real markets, the energy exchange happens on an hourly basis and thus the experiments for the model are divided into steps of 24 where each step represents an hour. This is one of the parameters `T` of the experiment. The experiments are repeated number of times for reducing the error margin and this value of 50 repetitions for each experiment is passed through the parameter `reps`. For different experiments, the `DecisionLogic`, `RewardLogic`, `EvaluationLogic` and `MeasurementGen` classes are also passed as parameters for the experiment as `dec_fct`, `rew_fct`, `eval_fct` and `meas_fct`. All these parameters of the experiment are passed as the `test` parameter of the `run_experiment` function. One of the examples of this `test` parameter is provided below.

```
tests_N= {"real":
        {"T":24,"reps":50, "dec_fct":DecisionLogic "rew_fct":RewardLogic,
        "eval_fct":NegoEvaluationLogic, "params":
                {"N":[20,50,100], "mu1":[1.01], "mu2":[1.37], "bias_low":[0.02],
                "bias_high":[0.8], "low_caste":[0.36], "tariff_avg":[1],
                "produce_avg":[1], "buy_low":[0.25], "buy_high":[0.48],
                "bias_degree":[0.5]}, "meas_fct":MeasurementGenReal}}
```

Every agent gets first value of perceptions from the `get_measurements` function of the `MeasurementGenReal` class. The agents in the model are divided into low caste and high caste based on the given parameter of `low caste`, which is the ratio of number of low caste members in the community in real world. This parameter is also passed through the `test` parameter of the function as the set of `params`. The other parameters which help in allocating the measurements to the agents as `mu1` and `mu2` as the averages of consumption for low and high caste, respectively. The proportion of agents who are biased (not ready to exchange energy with other caste) in the low and high caste are given by `bias_low` and `bias_high` parameters, respectively. The parameters of `buy_high` and `buy_low` give the proportion of the number of agents who can produce energy in high and low caste, respectively. The `bias_degree` parameter is the probability for a mediator to be biased (not allowing inter-caste energy exchange).

Based on this division of agents into low caste and high caste, the values of `production`, `consumption` and `tariff` are passed. For example, the mean value of `mu1` is allocated to the agents of low caste. Them a normal distribution around this mean value is generated and allocated randomly to agents of low caste for `consumption`. Similarly the production value is given to be 0 for low caste agents who cannot produce based on the `buy_low` proportion.

5.2. Modeling assumptions

Based on the information received from the literature and the constraints in agent based modeling as described in the Chapter 1, some assumptions were made for the model based on how it actually works in real life, and they are as follows:

1. In mediated agent based models, there are no possibilities for the agents to opt-out of the bid they have made. They have to accept what is offered to them by the supervisor if it satisfies their demand. This is how it happens in real life for large energy exchanges (e.g. at state/national grid level).

2. In case of discriminations among groups for energy sharing, the energy sharing happens via a supervisor in the group i.e. the main supervisor communicates with the supervisor in the group and the group members communicate further with the group supervisor. In real life, there is a head in the group who is usually an elderly member who takes decisions for the group.

3. The villages are divided into groups/ castes:

   (a) These groups can be formed due to difference in economic or professional status. Higher status groups usually have more income and thus higher resource allocations. Higher groups can trade these resources with everyone, but lower groups only share the resources within themselves.

   (b) There are N number of households and they are constant for different rounds, and ratio of high and low caste also remains constant.

4. There is an external check of the price to maintain a “reasonable price” which is used in agent based models in the internal market (market in the rural village setting itself is an assumed isolated market due to the decentralized system)

5. Surplus energy is stored by the producers in the batteries and this is put for selling/ trading.

6. Energy is wasted (as battery has limited capacity, and the battery can be charged every day except seasonal fluctuations - but the seasonal fluctuations are not considered here) if no partner is found while trading.

7. Entry and exit can have costs attached (new agents can enter at only start of new rounds), which is usual case in real life due to monopoly in the market.

8. Households usually have the payment scheme decided as pay as you go (pay largest chunk and then pay rest later) but the payment scheme is kept simple where the agents pay as they agree on a agent based model.

9. The economic status might change for agents due to energy exchange, but here it is assumed it would not in the model between the experiments.

10. Agents do not change their state across time, i.e. there is no influence on them from other agents to change their state except energy levels and the revenues/ payoffs. This also means that they only learn without expectations of any uncertainty in the market.

11. There are limited set of actions available for agents: buying and selling (bidding and accepting). The other types of actions (which are present in real world like renting, pay-as-you-go, etc.) are not included here. there are more than two castes in the community, but only upper and lower caste is included because the discrimination for the mediocre castes is not huge.

12. In reality, agents are typically buyer or seller only in reality, but here it is checked in every round if the production is higher than consumption or vice versa and then seller or buyer is decided.

13. Agents from higher castes tend to be seller than agents from lower castes and vice versa. There are some exceptions to do this, but for simplicity of the model, this is assumed.

14. Bid splitting is possible i.e. an offer of a large quantity can be split in several transactions; in other words an agent buy a part of an offered quantity

15. Some agents may sometimes buy from other groups: preference in the partner selection would be some form of probability

5.3. Data Selection

For the experiments to be conducted in the above settings, there is need of different datasets to deliver the model results as close as possible to reality. These datasets [2] are required for the parameters of `consumption`, `production`, `social_type`, and `tariff` values associated to agents. The types of datasets which are searched for each of these parameters are listed below. After browsing through various datasets available, the finalized datasets chosen are described below in sections 5.3.1-5.3.3.

1. For `consumption`, the data on load profiles is searched. Load profiles show the aggregate or individual loads/ energy consuming devices used by different people in a community. To understand the consumption patterns of the users, the load profiles give a good indication of the consumption patterns.

2. For `production`, the data on income distribution would be used. The production patterns of any community are based on the solar potential of the area, the affordability of the potential producer (to buy and maintain the storage), and the needs of the producer. The solar potential is constant (as the community lives in a very close region), and it can be considered that the needs and affordability are directly proportional to the income. Thus, the income value can be treated here as the indicator of production.

3. For `social_type`, social distribution data i.e. the distribution of people across castes in the community helps in understanding the cultural impact.

4. For `tariff`, the tariffs data in the national scale energy market can be used. The prices at which people trade is usually governed by an external price check i.e. the price at which market stabilizes in the national or regional market. This gives an indication of the price of trading by the users.

[2] Note that the choices of these particular datasets is also based on the access rights and ease of availability on internet

5.3.1. Consumption data

The different datasets which were searched for the consumption are listed in Table A.1. The final chosen load profile dataset is based on 2005 dataset from USA where the dataset is divided as per the different consumers with different economic backgrounds. The other complementary dataset from 2013 also gives the details of the consumption divided as per device, but it is rejected as there is no economic and class based division of consumption. Consumptions for 2005 dataset are much higher as compared to rural India consumption level. Thus scaling is done based on average consumption values (in 2005) of Indian household as given to be 470 kWh (compared to 13975 kWh of USA) [3].

1. The data is categorized based on different categories: 2005 Household Income Category, Income Relative to Poverty Line or Race of Householder
2. For each category, the type is defined in the column *Household*.
    - There are three main categories: Income Relative to Poverty Line(IPL), Race of Householder(RHA), and Household Income Category(HIC).
    - Then further, for example, the income relative to poverty is divided into three major types of households: Below 100 Percent, 100-150 percent and Above 150 percent. For this case study, these can translate to difference castes explained in the following section.
3. The *consumption* values are the aggregate consumption depicting the Energy Consumption Per Household Member (million Btu)
4. The *consumption* values are the aggregate expenditure depicting the Energy Expenditures3 Per Household Member (Dollars)
5. Finally, two additional measures of converted energy as per Indian standards (consumption in 2005) and the household type (castes) is included explained in the following paragraph of income datasets.

Table 5.1: Measures of consumption data

measure	description
IPL	Income Relative to Poverty Line
HIC	2005 Household Income Category
RHA	Race of Householder

5.3.2. Production and social data

As discussed above in Section 5.3, the production data is based on income, and the social data is based on the caste distribution. Two literatures were found which listed the incomes of different households (12000 households in different parts) distributed over different social types (castes) of India [61, 74]. Thus, these

[3] `https://data.worldbank.org/indicator/EG.USE.ELEC.KH.PC`

literatures are used together to calculate the production and the social data together. Considering the income data first,

1. The social parameter here includes differentiation based on two castes: "Dalits" which are the low caste and "others" which are high caste. These are the two main columns in the data. The column "proportion" just has ratio of the values for dalits with the others.

2. The data is distributed across 4 states: Andhra Pradesh (south of India), Uttar Pradesh (East of India), Rajasthan (Northwest of India), Maharashtra (Southwest of India).

3. The "measures" are explained in the table 5.2 below. Note that few of these measures are either explained as deciles or quartiles for combination of all states data or individual states, respectively. Also, for few measures, the complete data is used for the states individually e.g. means of incomes. Thus, the column "division" shows either order of the decile and quartile or whether the data is complete ("all").

Table 5.2: Measures of income data

Measures	**Description**
PIHD	Distribution of households by annual per capita income
PHPQ	Proportion of households belonging to different social groups in each quantile of per capita income
SIPD	share of total income accruing to persons in decile
SITD	share of total income accruing to households in decile
MITA	mean household income
EITA	median household income
PLHS	Proportion of households that own agricultural land
GCIV	Seller-buyer inequality Coefficient for village
GCID	Seller-buyer inequality Coefficient for district
GGIA	Difference between Income Gap and expenditure gap

The two datasets of the income and the consumption are merged here based on the ratios of the incomes. As explained above, the literatures which have given this data i.e. [61, 74] have income ratios for the dalits (low caste) to other(high caste). Similarly, the consumption data as explained in last section has division based on mean income. Looking at the measure "MITA" from Table 5.2 i.e. the income table, the average ratio of the income of the lower caste to higher caste is 0.3875. This means that the income of the higher castes is around 140% of the income of the lower castes. Looking at the consumptions measures from the Table 5.1 for "IPL" there are three categories: Below 100%, 100 to 150%, Above 150 Percent. So the ratio above 150%(which is closer to 140% mark) is used to depict the higher castes, and rest are the lower castes. Similar relation is used for the "HIC" measure from the Table 5.1.

The final conversion of income to production involves looking into consumptions as well. Production is possible only if income is at least able to payoff the cost of the production source. The sources are paid off in duration of around 5-6 months, with every month's cost around 1600 INR i.e. 23 euros (based on empirical study of last research thesis by author) for 8kWh. Based on the national surveys [4], the average rural house-

[4] http://www.ice360.in/en/projects/homepageservey/how-indians-spends

holds spend around 50% on essential goods and rest on services. Considering electricity as half of the total services, the income has to be at least 1.5 times the spending on electricity.

Thus, the income has to be at least 2400 INR per month i.e. 28800 per annum. Adjusting this to the 58% rise of price from 2005, the income has to be minimum 18230 INR. For ease of calculations, 20000 INR is included as the least income for production. Above 20000 INR, the 25% of income made proportional to the energy production as follows: for 20000 INR there 8kWh production daily (5000 INR spent on production), for 30000 INR there is 12kWh production (7500 INR spent on production). The "PIHD" measure (or PHPQ) in the Table 5.2 gives the range of income and for every range, the number of households in each caste are calculated (given the total number of households). Then these households are allocated randomly an income in this given range uniformly, and the production cost is also allocated based on the income as mentioned in the last paragraph.

5.3.3. Tariff data

Tariff data is rarely available and the only good source was ENTSOE (European Network of Transmission System Operators for Electricity) data from Germany. This has day-to-day updated hourly price rates per MWh of the traded electricity in the national market. The Tariff data is very straightforward giving the *timestamp* (for 24 hours on hourly basis) and the *Tariff rate* in the external market. Based on this data, from a normal distribution with a small standard deviation and the mean around these *tariff rate* value, the tariff rates are generated for the agents. The final column is the price converted in INR for per kWh. This is the value used for each round as mean of a normal distribution generated for different agents, and distributed randomly.

5.4. Conclusion

Based on the design of the models as listed in last chapter 4, this chapter described the details of implementation of the models. The first step for the implementation of the model was to run a basic model without real world scenarios or data implemented. This included laying down the framework of the model using the Python MESA framework and developing the different classes and implementing the logics of every function with repeated tests. Different experiments were developed by varying the `DecisionLogic` class, `partner_selection` function, and varying other parameters and similar classes. Once the basic model is implemented as expectations, the modeling assumptions are developed for feasibility of model implementation compared to the real world. Then the different datasets are searched for feeding the data to the perception of the agents. The consumption data is generated from 2005 load profiles of USA based on the economic classes. The inflation rate is included to convert the data to present. The production data with social data is generated from the recent literatures done in Indian context across 12000 households for income distributions based on castes. The tariff data is generated from recent data of tariff rate of ENTSOE from Germany. The results developed based on these real world implemented models is discussed in next Chapter 6.

6

Results

The chapter discusses the results obtained on implementation of the model, especially through sensitivity analysis on the results of the evaluation measures as discussed in Section 6.1. The analysis is extended on the mechanisms introduced in the model in Section 6.2, which compares the results for different mechanisms and the agents' properties and concludes the results. Section 6.3 helps checking the models for their robustness and validity based on some additional results of the model.

6.1. Sensitivity analysis for evaluation measures

The focus of the results will be on the obtained evaluation measures, as they check for the complete performance of the model. The trend of these values of the evaluation measures are discussed below for different experiments. Each of the result for different parameter of the experiments e.g. the total number of agents `N` is varied and the results based on it are discussed. Some other parameters whose variations lead to probable scenarios e.g. rise of consumption, production and tariff are discussed in the Section 6.3. After explanation of the different parameters used to explain the results in Section 6.1.1, Sections 6.1.2-6.1.6 explain these trends.

6.1.1. Results parameters

As a recap of evaluation measures as in Section 3.3, `wealth_distribution` is inequality for profits. Note that the wealth inequality is divided into `wealth_distribution_low` and `wealth_distribution_high` i.e. the inequality for profits of lower and higher caste. `Efficiency` is proportion of each demand/produce met/sold. `Seller-buyer inequality` is inequality of decisions (to be a buyer or a seller). `market_access` is the proportion of demands/produce met by the total demands/produce available. Market access is also divided as `market_access_low` and `market_access_high`). `Social welfare` is difference of rewards and costs and it is again split for higher and lower castes as `social_welfare_high` and `social_welfare_low`.

Based on the data gathered in the previous section 5.3, the results are obtained for the bilateral model, mediated model with addition of bid split and discriminatory mediation, as explained in Section 3.2. The results for bilateral are in "base" case. For the mediator, the results are shown in Experiment 1 to Experiment 4. Experiment 1 involves no bid splitting, and the mediator is not discriminatory, while Experiment 2 has bid splitting and mediator stays non-discriminatory. Experiment 3 and Experiment 4 has discriminatory mediator, but bid splitting present and absent, respectively.

6.1.2. Number of agents' variation

Seller-buyer inequality: Figures 6.1 show that increasing the number of agents has not a significant impact on the value of the seller-buyer inequality. The seller-buyer inequality is lowest for mediated non discriminatory model. For both the bid split models, the seller-buyer inequality is decreasing with increasing number of agents. For non bid split mediation, the seller-buyer inequality increases as N increases.

Social welfare: Figures 6.2 show that the social welfare increases for lower caste in mediation, especially for bid split mediation, while it decreases for higher caste for bid split mediation. Social welfare is the maximum lowest value of the reward and this means that in bid split as the number of agents increase, the maximum lowest reward increases for lower caste while decreases for higher caste. This might happen because the higher caste agents increase in number (0.36 is the low caste ratio here, making low caste a minority) as the number of agents increase.

Wealth inequality: Figures 6.1 show that similar to seller-buyer inequality, the wealth inequality also increases for non bid split, decreases for bid split and slightly increases for bilateral. The wealth inequality is best for the non discriminatory bid split with higher value of N. These trends are so because in bid split, more matched bids will be equal to the size of the bid chunks e.g. for the size of chunk of 0.1W, as there are more rewards proportional to this chunk size. In case of bid split, the wealth inequality equality for lowe caste is better for the bid split mediation and bilateral models than the higher caste.

Market access: Figures 6.2 show that the market access is better for lower caste always than the higher caste in case of mediated model. This is possible because of the low amount of bias with them and they willing to trade (buy/sell) with any agent they find. Market access is always increasing for the bid split mediation while always decreasing for the non bid split mediation. This is so because the bid split helps in better bid matching of the bids counting to more successes as compared to non bid split where the complete bids have to be matched and it becomes difficult with increasing number of agents. The bilateral model has higher market access for the higher caste than the lower caste because the biases of the agents are stronger in bilateral not allowing the lower caste agents to have enough access to market.

Efficiency: Figures 6.1 show that efficiency increases for the bid split mediations, while remains almost the same for bid split and bilateral markets. This is so because the bid split allows much better matching as all the bids have increased in numbers and all are almost the same size (chunk size).

6.1.3. Caste proportion variations

Seller-buyer inequality: Figures A.6a-A.6e show that the seller-buyer inequality decreases for bid split, especially for non discriminatory agent, with increase in lower caste agents' proportion. This is so because the increase in number of lower caste agents make the population more similar and the effect of biases reduce significantly when the bid sizes are almost the same.

Social welfare: Figures A.7a-A.7e show that the increase in low caste proportion increase the social welfare for the low caste and decrease it for higher caste in all the cases, and it makes sense because lower caste is the majority. But this also shows that the total social welfare decreases which means that the minority i.e. the higher caste has very low rewards as compared to lower caste when the proportion of latter increases.

Wealth inequality: Figures A.6a-A.6e show that the wealth inequality on average is always decreasing. But for the lower caste it decreases for bid split mediation only, and increases for the higher caste. For non bid split mediation, the trends reverse for higher and lower caste. For bilateral model, there is a slight increase in wealth inequality for both castes. This difference in higher and lower castes is possible when there is bid split because bid split allows maximum of the agents in low caste to have rewards when they are in majority. The population size of high caste agents is low with increasing low caste proportion. Thus, the seller-buyer inequality would be high for bid split as even small differences would give a high value of seller-buyer inequality for low population. For non bid split, the seller-buyer inequality would be higher for low caste as their population increase because there are more number of agents and the reward sizes are very different.

Market access: Figures A.7a-A.7e show that the market access is always increasing for bid split for both castes while decreasing for non bid split with increasing lower caste ratio. This again shows that the majority influences the overall market access especially when there is no bid split because the production and consumption bid matching is not very efficient.

Efficiency: Figures A.6a-A.6e show that the efficiency is highest for non discriminatory bid split and it increases for the bid split mediation with increasing low caste proportion for the same logic as seller-buyer inequality of similar population properties and easier trades without discrimination.

6.1.4. Agent Biases' variation

For bilateral experiments, the the proportion of agents who are biased in higher caste i.e. *bias_high* is one of the measure for the discrimination(by higher caste), while for mediated experiments the probability that the mediator will discriminate i.e. `bias_degree` is the additional measure for discrimination which will be discussed in next section.

Seller-buyer inequality: Figures A.8a-A.8e show that the increase in bias in higher caste increases seller-buyer inequality very slightly. The seller-buyer inequality is lowest for the mediated bid split without discrimination here.

Social welfare: The social welfare remains fairly constant for the mediated market with discrimination, increases in mediated bid split with no discrimination and first increases and then decreases for discriminatory mediation. It decreases for the bilateral models.

Wealth inequality: The wealth inequality increases and then decreases for the higher and lower caste as the discrimination in the higher caste increases. This is so because as the bias in the higher caste increases till 0.5, it restricts the agents to efficiently trade within, but after more than 50% agents are biased, they cause the gain of the access to the potential intra-caste market for both castes.

Market access: The market access first decreases and then increases for all the cases for higher and lower caste and even the overall market. This is so because the bias leads to reduction in access, but then the bias strengthens the inter-caste trade increasing the market access for the castes internally.

Efficiency: Figures A.8a-A.8e show that the increase in discrimination by the higher caste increases the efficiency for the mediated bid split model without discrimination. This is so because only in this case, the effect of the discrimination of the agents is not applicable and thus bid split can effect significantly.

6.1.5. Mediator biases' variation

Seller-buyer inequality: Figures A.10a-A.10e show that the bias increase in mediator increases the seller-buyer inequality significantly for the bid split with discrimination in mediation. There is no large effect on other values of seller-buyer inequality in other experiments.

Social welfare: The social welfare remains almost unaffected except for the general trend of slight increase and then decrease of the social welfare.

Wealth inequality: The wealth inequality always increase and for discriminated mediator. For non discriminatory mediator, it first increases and then decreases after reaching 50% chance of discrimination by the mediator.

Market access: The market access decreases for the discriminatory mediator. It first increases and then decreases for bid split mediation without discrimination and shows slight decline for mediated without discrimination and non bid split experiment.

Efficiency: The efficiency increases with the increasing bias in mediator for bid split mediation with discrimination, while decreases for the non bid split mediation with discrimination. When there is no discrimination in the mediator, the efficiency decreases for the mediated bid split model.

6.1.6. Producing proportion variations

Seller-buyer inequality: Figures A.12a-A.12e show that the increase in proportion of agents who can produce in lower caste always reduce the seller-buyer inequality value. The seller-buyer inequality is lowest for non discriminatory mediation in bid split. This is so because the increase in production level of lower caste in bid split allows more sellers in the market.

Social welfare: Figures A.13a-A.13e show that the social welfare always decrease for the mediated for the high caste and it always remain same or increase for the lower caste. This is so because as the production of the lower caste increase they can produce more and thus maintain good minimum rewards. As the rewards of the lower caste increase, the majority of the higher caste shifts to the lower rewards (as the least reward is not increasing) and thus the least reward (which is social welfare) goes to the higher caste agent.

Wealth inequality: Figures A.12a-A.12e shows better results for mediated model with increasing production level of lower caste because of more produce available in the market and more equal distribution of rewards. In case of bid split the wealth inequality is good for lower caste as compared to the non bid split because (where higher caste has more equal distribution) because the rewards get more equally distributed in case of the bid split for even the low caste.

Market access: Figures A.13a-A.13e show that the market access always increase because the market has more produce to satisfy the demands in such a market. In case of non discriminatory model in non bid split, the market access increases for lower caste and decreases for higher caste. This is so because the producers who have more produce can sell more, and those who are poor (higher caste) cannot sell but just buy in most cases. While for the discriminatory model in non bid split, the market access first increases and then decreases. This is so because the higher caste is not ready to trade with the lower caste so this stops transactions as the lower castes get to produce more and thus reduces overall market access.

Efficiency: Figures A.12a-A.12e show that the efficiency increases for bid split, but only slightly increases for other cases. This is so because the production is increasing and in case of bid split it allows more ease of bid matching.

6.1.7. Consumption and Production variations

Additional to the above results, further results are compared in this section to check the sensitivity of the model based on the varying parameters in section 6.1.7.Here, a one-factor method testing is used for a form of sensitivity analysis. In other words, the only parameter on the x-axis of the graphs in varied and all other parameters are kept the same to check the evaluation measures like the above results. The model is said to be robust if behavior of the model does not change largely across experiments and parameters.

Consumption Variation: Figures A.14a-A.15e show that the increase in the mean of the consumption of the low caste keep the behaviors of all the results constant across experiments. It can be seen that the trends of the evaluation measures are also not very sensitive to the varying parameter of the consumption. The seller-buyer inequality and wealth inequality is increasing for bid split and bilateral models and decreasing for all other experiments. The efficiency has just an opposite trend. The market access and social welfare have similar decreasing trends for bid split and bilateral model, while increasing for non bid split.

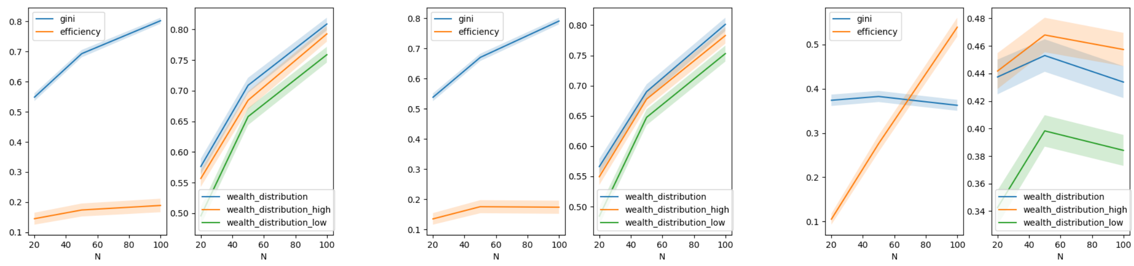
Production and tariff variation: Figures A.16a-A.18e does not show sensitivity towards the parameter value except for the market access, efficiency and wealth inequality for the bid split model with changes in the behavior as the parameter value increases. But the model stays non sensitive to the other evaluation measures like the seller-buyer inequality and social welfare. Except for these experiments, the models have shown to be robust i.e. there is no changes in behaviors due to parameter changes. The seller-buyer inequality decreases for production increase and remains same for tariff changes. The social welfare remains fairly constant for these changes too.

6.1.8. Conclusion: Comparison of evaluations

Evaluation measure results for increase in number of agents are considered here as case in-point and the results are shown in the Figures 6.2-6.2.The figures here clearly show the trends as were discussed in the section 6.1.2. The focus of this section to understand the differences between different mechanisms, especially the social welfare versus market access, and seller versus income inequality among different experiments. The effect of bid split in different evaluation measures are shown in 6.1. It can be clearly seen that the effect of the bid split on the seller buyer inequality is higher than the wealth inequality effect. Also, the effect on the market access of the bid split is very high compared to the social welfare effect, proving the hypothesis right.

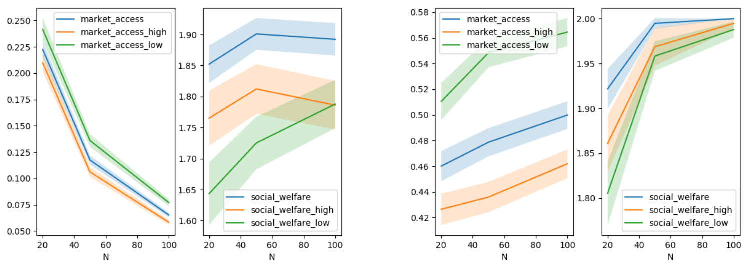
Table 6.1: Percentage increase of evaluation measures with bid split for non discriminatory(nd) and discriminatory mediation(d)

		seller buyer inequality	wealth inequality	social welfare	market access
N=20	nd	0.30	0.23	0.02	0.49
N=20	d	0.33	0.24	0.04	0.52
N=50	nd	0.43	0.34	0.07	0.72
N=50	d	0.47	0.39	0.05	0.75
N=100	nd	0.54	0.46	0.06	0.86
N=100	d	0.54	0.46	0.05	0.87



(a) Bilateral (b) Mediated (c) Mediated bid split

Figure 6.1: Gini(seller-buyer inequality), Efficiency and wealth distribution(wealth inequality) with N variation



(a) Mediated discrimination (b) Mediated bid split discrimination

Figure 6.2: Market access and social welfare with N variation

6.2. Sensitivity analysis for mechanisms

Now that all the individual results are know, this section will describe the differences in the results for different experiments. The avergae results will be compared for significance difference and the results are shown in Table A.2-A.4. The results for different sets of experiments, like bid split versus non-bid split, discrimination versus non-discrimination in mediation, and bilateral versus mediated transactions are compared in section 6.2.3-6.2.2. Finally some detailed analysis will be done over important evaluation measures for lower and higher castes in section 6.2.4. All the experiments are compared to answer the third sub research question on which experiment performs the best for the evaluation measures. All the results show that there is significant difference between the experiments (e.g. the social welfare for low caste), and this is checked with the ANOVA tests, as in Table A.5.

6.2.1. Bid-split versus non bid-split

- The seller-buyer inequality for bid split is better than that for the non bid split because bid split allows more sellers and buyers in the market, especially the former. This reduces the seller-buyer inequality value for the bid split experiments.
- The average social welfare is higher with the bid splitting. This is so because bid split allows to raise the minimum utility of the experiments as more agents can get rewards now who produce less.
- For bid split, the wealth inequality is lower as compared to non bid splits. This is due to increased

distribution of equal rewards among the agents, reducing the value of the wealth inequality inequality.

- Market access increases 7-8 times for bid split experiments because the low producing agents can now also trade in the market.
- The efficiency of the experiments increase around 2 times with bid splits because every bid is divided into small chunks and all of these chunks can be met one by one accurately with bid split experiments.

6.2.2. Discriminatory versus non-discriminatory mediator

- The non discriminatory mediation gives a better seller-buyer inequality value (i.e. lower value) because the non discriminatory mediator does not have any biases allowing more fair trade, and allowing equal distribution of sellers and buyers in market, especially increasing buyers.
- The social welfare is again better for non discriminatory mediation because of reduced biases allowing more low-producing agents to have a higher reward.
- The wealth inequality is better for non discriminatory mediation similar to seller-buyer inequality because of more equal distribution of rewards without any biases.
- The market access remains better for the non-discrimination of the mediator. This is so because number of agents who can access market or trade energy are much more when there is no discrimination.
- Finally, the efficiency is also better for non discriminatory mediation because of no biases allowing more demands to be met.

6.2.3. Bilateral versus Mediated

For all evaluation measures, the bilateral model performs the worst compared to the mediated model, even compared to the mediated discriminatory and non-bid split model. This is as per the hypothesis that due to strong discriminations among the agents, the market access and seller inequality is very low and very high respectively for bilateral model. The inefficient trading in peer-to-peer (bilateral) trading reduces the efficiency of the model as well. It should be noted though that the difference in the worst performing mediated model (discriminatory and non bid split) and bilateral model is not very high. But the bilateral model has very low efficiency as compared to other models.

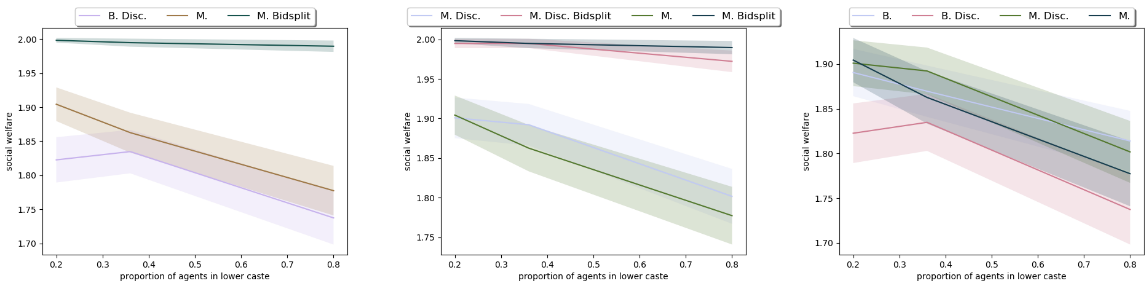
6.2.4. Lower versus higher castes

The social welfare is also higher for the lower castes than the higher castes in case of all mediated results. This is so because the higher castes are a majority and the distribution of rewards get more broader in case of majority. This trend can be seen reversed in the low caste ratio increased, thus proving this hypothesis. The wealth inequality reduces almost to half for the lower caste with bid split and also significantly for higher caste. The reduction is much lower for the lower caste because none of them get any opportunity in the non bid split market, while they get market access in the bid split market. This can be seen with a high increase in the market access values as well.

6.2.5. Conclusion: Comparison of mechanisms

The above sections have already discussed the hypothesis around the results of the evaluation measures. The further hypotheses on comparison of evaluations and comparison of the mechanisms are discussed here. For comparing the effects of different mechanisms, the results are laid down in Figure 6.3, showing social welfare and seller-buyer inequality results for increase in proportion of low caste agents. As can be seen in the figure 6.3a, when there is no discrimination (except bilateral model), the effect of mediation is much lower than the effect of the bid split. As can be seen in Figure 6.3b, again the effects of the bid split are very high as compared to the elimination of discrimination only.

Finally, the Figure 6.3c show all these results in one frame. One interesting trend here is that the difference in bilateral and mediated model is low, while the difference in bilateral discriminatory and mediated discriminatory model is high. Also, the effect of discrimination on bilateral is much higher than the effect of discrimination on mediation. These trends were not hypothesized and thus will be discussed further in the validation section 6.3.1. Some of the other results on comparison of mechanisms are shown in Appendix Figures A.19a-A.22c.



(a) Mediation vs bid split (b) No discrimination versus bid split (c) Mediation vs no discrimination

Figure 6.3: Social Welfare across variation of low caste proportion

Exceptional behaviors: There were also some very particular case-wise exceptions to the hypothesis and the trends which are discussed above. Some of these exceptions arise due to the real situations, while others arise due to the specific model setting. The first exception if that if the consumption is very high for high caste, then the efficiency for mediated discriminatory performs worse than bilateral. This is so because when the consumption is high the demand for the high caste cannot be met due to discriminatory mediator (which does not allow any form of inter-caste trade). This shows that the mediation (with discrimination) is not very effective to reduce inequality between rewards of agents in different castes. Another exception of the model is that if the probability of discrimination by mediator is higher then the mediation with discrimination has worst results (very close to bilateral) in most evaluations. This is expected because as the mediator becomes more discriminatory it does not allow any inter-caste trade, worsening the results.

The third exception, which is due to the model setting and not necessarily the real world setting is that the social welfare is low for high caste for the mediated non bid split models than the bilateral, when the proportion of low caste increases. If it is around 50% then both the high and low caste suffer. This shows that the majority plays an important role in affecting the results of the model. Basically, an increasing majority of a caste makes the model trade the rewards from the minority. This may or may not happen in the real world. The final exception, also due to the model setting, is that the wealth inequality for many cases is high for the mediated discrimination than the bilateral model.

6.3. Validation

The section 6.3.1 aim to validate the model by comparing the actions of the models based on changing model parameters and expert interviews in section 6.3.2.

6.3.1. Market model validation

The market model validation is done in this section i.e. the general trends in the market are compared with the trends of the model. The market model validation involves checking the effects of production, consumption and tariff on sales, where sales is defined as the action or the number of sellers and buyers in the market (higher *action* value is given to sellers than the buyers). The production increase, increases the actions i.e. the number of buyers an especially sellers increase. As the consumption increase, the actions decrease i.e. the number of sellers increase and the number of producers increase. This is so because their are more divided sellers and buyers than just sellers.

Even if the models behave as expected in the hypotheses, there are some trends which need to be analyzed for significance of their correlations, to understand how much the results are due to the model design. To do this, the different aspects of the mechanisms from the model design, namely mediation, no discrimination, and bid split effects are discussed one by one in the following paragraphs. As seen in figure 6.3 and the results in Appendix, the maximum effect on improving social welfares come from the bid split, followed by similar effects from mediation and removing discrimination. Here, the "effect" means the difference in the evaluation measure achieved by the mechanism from the base scenario (bilateral discrimination).

Mediation and No-discrimination effect Removing discrimination has lowest effects on the evaluation measures as can also be seen in Figure 6.3 above. As can be seen in the figure 6.3c, the effects due to introduction of no discrimination in the base scenario are slightly better than mediation. But note that, such a situation is not realistic and thus mediation is introduced. The purpose of the bilateral model without discrimination is to compare the effects of discrimination on the model. Also, the effect of no discrimination is much higher than the effect of no discrimination on the mediator. Here, the difference in bilateral and mediated models without discrimination is low, while the difference in bilateral discriminatory and mediated discriminatory model is high.

The mediation leads to a much better efficiency because of better partner selection and bid matching as compared to a bilateral model. This can be seen in the Figure 6.4b. The mediation allows for a better partner selection and thus also increases the market access for the model. But compared with simply a non-discriminatory bilateral model, the effects are not very different. This shows that the advantage (considering the evaluation measures) achieved from a mediated or a bilateral model is similar, if there is no discrimination.

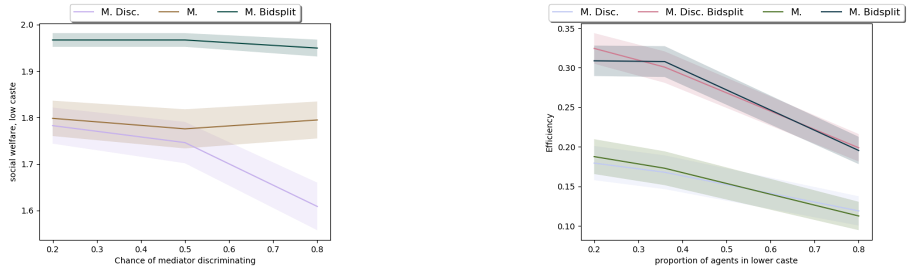
The reason for this is that (as mentioned earlier in section 3.2.1) the discrimination is modeled in two ways: for the agents, and for the mediator. Both of these discriminations are modeled probabilistically i.e. the discrimination happens by chance in every experiment. The direct effect of the chance based discrimination in case of mediation is only on mediator, while in case of bilateral model, the direct effect is on the agents. In reality, this is expected that due to the presence of even a discriminated mediator, the effect of discrimination are reduced significantly as agents are not discriminating directly. The results of variation in the discrimination can be seen in Figures 6.4a. The correlation effects of increase in discrimination on decrease of market access, social welfare and efficiency, and increase of inequalities are given in table 6.2 below. It can be seen that the correlation to the bid split of increasing discrimination is highest on the social welfare and wealth distribution, where the rewards are allocated to the agents. Thus model results of models are dependent on the reward sizes and allocation strategy.

Table 6.2: Pearson correlation coefficient of evaluation measures with increasing chances of discrimination of mediator

	social welfare	market access	efficiency	wealth inequality	gini
discrimination with bid split	-0.96	-0.92	-0.80	0.96	0.90

Bid Split effect The bid split has the maximum effect to prevent discrimination in energy trading. It is due to several reasons, e.g. small consumers are those who get benefited more from bid split than the larger consumers and thus the evaluation measures are better for bid split, providing more equality. This can be claimed based on the higher increase in market access in low caste, as compared to high caste, after introduction of bid split. The seller-buyer inequality also reduces heavily with introduction of bid split, as more people are able to buy (even if they have very small demands which they can afford). The rewards for the lower castes are still not very high as can be looked by the social welfare, but at the same time bid split helps in increase of the social welfare for all.

There are some parameters in the bid split to be considered which significantly affects the results. The size of the chunks of the bid split significantly effect the bid split. Also, in the algorithm design, it is very important to update the allocation of partners and the satisfaction of demand with every round. For example, if a consumer demands 5 W and is provided 1 W in the first round, it is important to update that the consumer still needs to fulfill the demand of remaining 4 W. This is unlike the normal partner allocation, where the allocation of partner is done one-off.



(a) Social welfare for bias degree variation

(b) Efficiency for proportion of lower caste variation

Figure 6.4: Validation measures

6.3.2. Expert validation

For further validation, the results obtained were discussed with four major experts, to understand the feasibility or applicability of the solutions and the correctness of the solution.

Interviewees: For the former, a micro-grid project leaders in India (Rural Spark[1]) deploying solar energy panels and allowing energy sharing through sharable batteries was interviewed. Next, a leader of the company installing Solar Home Systems in urban poor areas was introduced[2] Next, a researcher working on anthropology to understand social dynamics was also interviewed from Design Studio Lab in TU Delft (IDE, [3]) The other interviews were done with academicians to understand the correctness of the proposed solutions and the results. One of them is researcher in Computational Social Science Group at ETH Zurich working on decentralised energy systems (COSS [4]). The other is researcher in DC systems group at TU Delft (DCE&S, [5]) working on the feasibility of energy exchange in rural regions of developing countries.

Questionnaire: The discussions for expert validation had the questions presented in sets as per their respective expertise. The first set was about the definitions of evaluation measures and different functions in the thesis For example, the questions included "what are the limitations of discrimination, market access and efficiency definitions? How the definitions can be improved for further research? What kind of factors would change these solutions significantly because of the definition e.g. temporal effects is one of the factors which is not included in the definition." The next set of questions was more technical where the costs/ technical issues/benefits due to mediation were discussed, also limitations of the systems (technical issues) to tackle such automation mechanisms – especially bid splitting were discussed. Finally, the feasibility of mediated discrimination and which among the automation/human about would be easier was discussed.

The next set of questions were on design of the model i.e. the decision and bid split design e.g. limitations in form of partner selection. Also, other ways to capture cultural effects in models and especially learnings of

[1] www.ruralspark.com
[2] www.piconergy.com
[3] http://studiolab.ide.tudelft.nl/studiolab/
[4] https://www.coss.ethz.ch
[5] https://www.tudelft.nl/en/eemcs/the-faculty/departments/electrical-sustainable-energy/dc-systems-energy-conversion-storage/

the agents, were discussed. This was followed up with dscussion over results i.e. any expected versus observed correlation between demand/ production/ tariff rise and decisions. Finally, social validation in terms of how people would accept the solutions and are there differences in automation versus human interventions, were discussed

Results: Based on five separate discussions and the above laid questions, inputs were gathered on the assumptions of the model. The assumption related to the discrimination in India in energy trading was confirmed by researches [71]. It was suggested that the definition of discrimination can be extended. This can be done by including the effects of "peer pressure" within the intra caste. These intra-caste bonds are strong and to maintain these relations within their own caste, people tend to discriminate more based on peer pressure.

The another assumption around the discrimination by mediators was also discussed. It was suggested that as the systems scale up, the chances for discrimination by the mediators increase (for personal profit or favoritism towards a society e.g. the rich caste). It was suggested that the market decision model serves as a good basic model for now, but it misses on capturing the normal electricity market problems and they are the peak, volatility of the prices and congestion in the market. The other market issues like the formation of cartel by some of the agents, and uprising of black markets are common scenario in local markets, and should be used in uncertainty modeling as well.

Coming to the technical implementation of the mechanisms suggested in the thesis, it was suggested that the bid split should not be done such that the chunk size of the bid split is very low. If the bid split is done such that the chunk size is very small, it would prevent the larger appliances to run at all. Thus, it is very important to consider the end appliances/ demand load critically in the model. For example, 50 W bulb will not run for a consumer if only 5 W of demand is met for the consumer. But this problem is significant only if the trade is happening in really small community (10 households) and this might not be a big problem in case of a large scale system e.g. around 1000 households.

6.4. Conclusion

The chapter presents various results based on the five sets of experiments performed for the bilateral, mediated with/without bid split and with/without discriminatory mediation. The results are discussed especially for the evaluation measures of the seller-buyer inequality, social welfare, market access, wealth inequality and efficiency measures. The results are first discussed based on the different variations of the parameters and all of these trends show pretty robust results i.e. similar behaviors across repetitions of experiments. The different parameters which are varied are the number of agents in the model, the low and high caste proportions, the biases of the agents and the mediator and the producing population proportion. To further check the validity and robustness of the model, other parameters of the consumption, production and tariff means are varied for the complete population and the results of evaluation measures and the decisions are checked. The models look to be robust and valid as per the expected behaviors.

The final discussion of results conclude that the bid split models are performing much better than the non bid split models. The non discriminatory mediation is much better than discriminatory mediation especially for the equality measures. Then, the lower caste looks to be benefited more from these mechanisms than the higher caste, while the higher caste is not at any losses. The mediated model always perform better except for the mediated non bid split which looks to perform more unequally for the seller-buyer inequality and wealth inequality because of slight but not enough increase in number of sellers. Thus it is concluded that the mediated bid split without discrimination performs best. Other trends around model results are discussed in Chapter 7.

7

Discussion and conclusion

The conclusion of this thesis will be structured up as per answering the research questions. As discussed in Chapter 1, the main research question of thesis is: *"How different mechanisms affect reduction of discrimination and optimizing efficiency in the setting of energy trading in rural India?"* To answer this, the research question is further divided into various parts, and the first question aims at answering: *What are the issues with the existing solutions with respect to discrimination and efficiency in energy trading?* Based on the discussion in Chapter 1, the major issues can be seen in the India's energy local market around discrimination of energy sharing due to social groups. The markets here are the bilateral i.e. peer-to-peer energy trading markets, where the agents sell the energy to each other directly.

The Chapter 2 looks into depth of different agent based models which can help model these communities in India as a market model with energy as a resource being traded. The zero intelligence agents are chosen here to develop the agent based models. The agents are motivated by profits and decide their bidding strategies as per their profits and costs in the earlier rounds. Agents learn or take actions, as discussed in Section 2.3, based on the evolutionary switching mechanisms here, i.e. based on their own relative performances. Coming to the market models, the market design is studied in literature for both financial markets and energy markets. Based out of all strategies, the strategy as laid out in [38] of ordering of bids is implemented. Here, as discussed in Section 2.4, an order chart is made as per the bids by the buyers and the sellers. The top (lowest) sell is matched with the top(highest) buy, and so on, and then transactions are done. The bid prices are randomly chosen in the given range and the bids are updated every round.

To answer the next research question on: *What cultural models and market models fit best to the current scenario, capturing trade-offs in efficiency and discrimination?* Mechanisms to minimize discrimination effect in the community are laid out in the Chapter 3. These mechanisms are introduction of a mediator in the trading, such that the mediator can prevent the biases (discrimination i.e. not trading with each other based on different social group) by the agents. But the mediator can be discriminatory itself and this is also introduced as a mechanism for the experiments. The final mechanism introduced is that of bid splitting which splits the bids into equal chunks of production and consumption bids. This does not let the agents to discriminate based on the different bid sizes. Different parameters for the model evaluation are laid out in Chapter 3 which check how these mechanisms perform. The design of the model is laid out in Chapter 4 where all the functions used for developing the models are explained in detail. Finally, to answer the last research question: *How do different models perform for the measures of efficiency and discrimination?*, the following sections are introduced which would discuss and compare all results. This will help answering the overall research question in the section 7.2: "How different mechanisms affect reduction of discrimination and optimizing efficiency in the setting of energy trading in rural India?"

7.1. Discussion of results

The hypothesis on every evaluation measure as explained in the Section 3.4 can now be checked as the complete results are available. The hypothesis for all the evaluation measures were that the mediated bid split without discrimination would perform the best for all the different experiments, which was proven right. But additional to the best performance of the mediated bid split non discriminatory model, there are some more interesting trends which were noticed in the results of the experiments and also revealed during the validation of the model (with experts and modeling validation). These trends, affect the hypothesis of the model and thus are important and discussed below.

7.1.1. Evaluation results on mechanisms

Mediated bid split without discrimination as the best performing model: This means that all the different evaluation measures namely market access, social welfare and efficiency would improve due to introduction of the mediation without any discrimination by the mediator and the bid splitting mechanisms. At the same time, the seller-buyer inequality (the inequality among the number of sellers in the market) and the wealth inequality would reduce. From the results as discussed in detail in Chapter 6, it can be seen that these hypotheses are proven correct via the model. The definition of the evaluation parameters, especially social welfare and market access, and the definition of discrimination plays a very important role here in governing the results as checked in the validation.

Bid split has higher benefits than mediated alone: When the bid splitting results are compared with the effects of introduction of mediation alone, it can be clearly seen that the former has higher impacts on evaluations, especially increasing market access and reducing seller-buyer inequality. The effects on social welfare and wealth inequality are not significantly higher for bid split with mediation alone, because they are associated with allocation of rewards. The rewards are directly proportional to the production capacity of the agents, and as the production capacity of lower caste is much lower, the inequality reduces, but still remains with the introduction of bid split.

Bilateral better than non bid split mediation for market access: Bilateral models here are designed such that every agent in each round only gets allocated to one partner in a given round even if there is excess of the energy with the seller. But in case of mediated non bid split model a seller agent can get allocated to more than one buyer agent. This is particularly interesting for market access, because mediated models can lead to reduction of number of sellers because of such allocations. For mediated bid split model, the equal bid allows many agents to be sellers and thus again increase the market access of the model. This assumption is made so because i reality this makes sense. When there is bilateral matching, the agents have high cost to go to everyone's house to sell the excess, so it just finds a good match and sells to them and does not repeat the bid matching and find other agents for selling excess.

Bid split makes lower caste winner: The lower caste has much lower inequality in terms of rewards and much higher social welfare as compared to non bid split experiments. The higher caste also gains from this, but not to the extent the lower caste does for social welfare (e.g. the wealth inequality almost reduces to half for lower caste and approximately one-third for higher caste). In case of market access, the higher caste and lower caste both are equally affected.

7.1.2. Community learnings

Favoring only one caste does not help the community: Majority (the caste with more number of agents) plays an important role to decide not just the total trends, but also some of the trends of the other caste. As seen in the results, when lower caste proportion who can produce increases, the higher caste social welfare decreases. This means that uplifting just one segment of community does not help the community, till the actual minimum social welfare is lifted - and this is only possible with increasing production of everyone. The difference of social welfare and market access becomes very low for the increase in production for all.

Bias can help market access to increase intra-caste trade: Bias increase among the agents help to increase market access because there is more uniform population. Bu this only happens after the bias is more than 50% of the population i.e. almost everyone is biased and wants to only trade internally. Such results are not seen in the mediator discrimination and only are possible when there are biases of the agents.

Agents behavior effects: The consumption, production and the variations of other parameters like the proportion of agents who can produce among the lower castes are varied to replicate the future potential scenarios. As can be seen in these cases, very high production values reduce the market access for the mediated model (as per the above explanation), and thus make bilateral markets with highest access. Still the bid splitting markets perform very well and thus it is recommended to implement bid splitting mediation in high production. The high consumption increases market access for mediation by the similar logic and thus the best solution is always that the production and consumption should increase proportionately for maintaining similar results and not avoiding market access losses for non bid split mediations.

7.2. Policy Recommendations

Based on the discussions of the main results obtained above, finally the overarching research question can be answered: "How different mechanisms affect reduction of discrimination and optimizing efficiency in the setting of energy trading in rural India?" The primary answer to this question is that introduction of bid splitting mechanism and introduction of local mediation, can prevent discrimination and help in more efficient and "fair" energy trading. The detailed answer is provided via recommendations below. Note that these recommendations are directed mostly towards the start-ups/ businesses introducing bilateral energy trading in developing parts of the world (especially, rural India) with presence of high socio-economic discrimination in the community. Also, the local policymakers (governments) and NGOs can undertake some of these recommendations generally towards the energy access projects (e.g. the Solar Home Systems installation projects).

7.2.1. Introduction of mechanisms

Improves access, not rewards: The bid splitting mechanism works very well for giving access to the agents, especially from lower caste with a low produce, to trade energy in the market. As the rewards are proportional to the produce, the lower castes do not have a significantly high social welfare, but it definitely improves, and also similar results hold for wealth inequality. Thus, it is important to understand that these mechanisms are aimed at improving access for all, and create a more "fair" market for ease of entry for low energy producers. But in no way these results ensure higher rewards, and thus more measures need to be introduced for higher rewards. Some of such measures were discussed in previous thesis done by the author [70] e.g. introducing a "barter" system allowing trade of goods or services like maintenance of grids (instead of money) in return of energy.

Need of automated approach: The effects of bid split are much higher than effects of the mediation alone on the evaluation measures of access, welfare and efficiency. At the same time, the bid split can only be introduced in case of mediated energy trading, and thus maximum efforts should be taken to automate this mediation to (a) reduce the effects of the discrimination by mediator (the effects of discrimination alone discussed in section 7.2.2), and (b) the bid split can be effectively implemented only with an automated approach (e.g. when there are higher number of agents in the community), and as bid split is based on mediation, it should be implemented with an automation device (e.g. a distribution controller/ optimizer).

Need of high efficiency for mechanisms to work: If an agent has a demand of 5kW for a device, and by the bid split mechanism, the agent is only offered 0.1 kW, it will look to be a successful transaction. But in reality, the agent would not be able to run the device, and thus it is a wastage of the energy traded. Thus, there are three ways to tackle this (1) efforts should be put towards low wattage devices and thus ensure that lowest producers can enter market, (2) the bid split size of chunk should be adjusted as per the demand of the devices, (3) there is also a possibility of cartel formation for very low energy producers, but this would also demand high regulation to ensure any emergence of oligopoly markets.

Effects of mediation and centralization: The idea of introducing mediator in the bilateral energy trading i.e. a decentralized energy system looks to be counter-intuitive. Also, during the discussions with experts, this was discussed as a major concern. But it should be noted, that the aim of the thesis is to facilitate energy trading in a decentralized network itself, where, mediation acts as a temporary step to bring anonymity in the network and overcome the discrimination between the agents. At the same time, the effects of even a local centralization or mediation, should be considered with high precaution, as it is seen in past experiences (as explained by experts) that the introduction of central, or even micro-grids, have eliminated the local markets or led to formation of black markets and formation of cartels.

7.2.2. Social interventions

The model results and validation have shown that the prevention of discrimination can already help fairer energy trading and save costs of implementation of these new mechanisms, to some extent. Added to the analysis and measures below, measures can also be introduced through community awareness, education campaigns, as interventions from NGOs/ government.

Importance of focus on reduction of bilateral discrimination The most important assumption of the complete thesis was that the discrimination in the bilateral energy trading cannot be removed due to the existing social norms and unavoidable social interaction among traders. Still such a model was constructed for sake of comparison. It was clearly seen that the effects of removing discrimination already achieves the results of lowered inequality and higher efficiency, social welfare and market access. These results are very close to the results from the mediated energy trading (without discrimination), and would help in cost cutting. This shows importance of policy efforts on reduction of discrimination in current bilateral energy trading settings.

The effects of peer pressure on discrimination: During validation of the model with experts, a very important point was noted about the origin of discrimination in the community, which is beyond the scope of thesis, but worth considering while implementing mechanisms from this thesis. The inter-caste discrimination is strengthened in community due to strong intra-caste bonds, and thus this is one at the first place by people to "please" members of their own caste (favoring own caste over others). This is a form of learning mechanism which is important driver in the community and thus should be modeled and considered further.

7.3. Limitations and further work

The results, as discussed above, are highly affected by methods used for the implementation of the model. As discussed in Table 1.1, the most important method used in this model is agent based modeling (ABM). The reasons why ABM are chosen is explained in Chapter 1. The modeling assumption and data selection, along with model design as in Chapter 4-5 also help in reflecting on the results.

To answer these research question, different methods and datasets are used for implementation. Though ABM is the best choice for this thesis because of different behaviors of the agent easily captured, the method has its own limitations which give scope of improvement and further research. Additionally, the modeling assumptions and data selection limit the thesis results as well. These limitations and scope of further research is discussed below.

7.3.1. Limitations of method

1. The choice of the agent based models limits to model any other external effects on the model. For example, the agent is limited to the learning only from its social choices. The economic priorities of the agents of the community are not given much importance in the model, but in the real world this is not true and this should be improved for further modeling.

2. Some scenarios of high uncertainty can lead to complete failing of these mechanisms. For example, the grid extension to the community might lead to eradication of the bilateral energy sharing and thus make these mechanisms useless. So policies towards adaptation to such scenarios should be modeled as well.

7.3.2. Limitation of results

The results that are obtained in this thesis are valid in the context when the assumptions hold and also for the given choice of algorithms. In case, the assumptions do not hold correct or the choice of algorithms is different, many results might not be the same. These give limitations and future scope to the work:

1. The discrimination modeled here is a social parameter and thus very subjective to different types of communities in rural India. Thus, the definition of discrimination does not remain same for all. Also, some communities have no only caste based discrimination, some have additional layer of religion and economic status, while some have none. Thus, such variations are very difficult to be captured in the model and also, hard to capture in simulation settings. One of the (lengthy) ways to solve this is to introduce all the different types of discrimination and based on every community, run different simulations, choosing the appropriate combinations of discriminations.

2. The decision algorithms here which lead to partner selection here are based on ordering of bids based on the tariff rates and allocation based on consumption and production needs. As discussed in the literature review in Section 2.4, there are multiple other ways of partner selection. These different al-

gorithms, highly effect the evaluation measures and thus different algorithms, especially which are already applied successfully in the central level grids should be tested here. Also, the evaluation measures here considered are limited to one definitions, and thus the relation between different definitions of evaluation measures and algorithm choices should be considered.

3. There are different challenges in implementation means of the solutions as discussed in the Section 6.3.2 e.g. the emergence of cartels, black markets in the energy trading are very probable scenarios in local market. Most of this happen because of the possibility of high discrimination by the mediator. Thus, mechanisms to prevent mediator's control on the system needs to be considered.

A

Additional figures, listings and tables

Listing A.1: Bilateral Partner Selection

```
for every agent in set of agents:
        Allocate the "seller" or "buyer" status to the agent
        if agent has "seller" status:
                Add it to the list of sellers
        else:
                Add it to the list of buyers
        Sort sellers with ascending order for tariff
        Sort buyers with descending order for tariffs
        Check in order:
        Repeat this till the production/consumption of agent/partner finishes:
                if production of seller matches consumption of buyer
                        Allocate partner
                else
                        go to next agent
Return partner of the agent
```

Listing A.2: Mediated Partner Selection

```
for agent in set of agents:
        Allocate the "seller" or "buyer" status to the agent
        Calculate the costs for the agent
        if agent has "seller" status:
                Add it to the list of sellers
        else:
                Add it to the list of buyers
        Sort sellers with ascending order for tariff
        Sort buyers with descending order for tariffs
        Calculate "r" as minimum of length of sellers and buyers
        while True:
                if seller<r and buyer<r and r>=1:
                        k = seller production - buyer consumption
                if k=0:
                if production of seller matches consumption of buyer
                        Allocate partner
                else
                        go to next agent
                Update seller production and buyers consumptio to 0
                if k>0:
                        if production of seller matches consumption of buyer
                                Allocate partner
                        else
                                go to next agent in buyers
                        if seller sells everything:
                                go to next agent
                Update buyers old consumption to transacted consumption
                Update sellers production to difference of current production -
                and met consumption
                if k <0:
                        repeat the above process of k>0 for seller and buyer swaped
Return list of allocated partners to each agent
```

Listing A.3: MeasurementsGenReal class

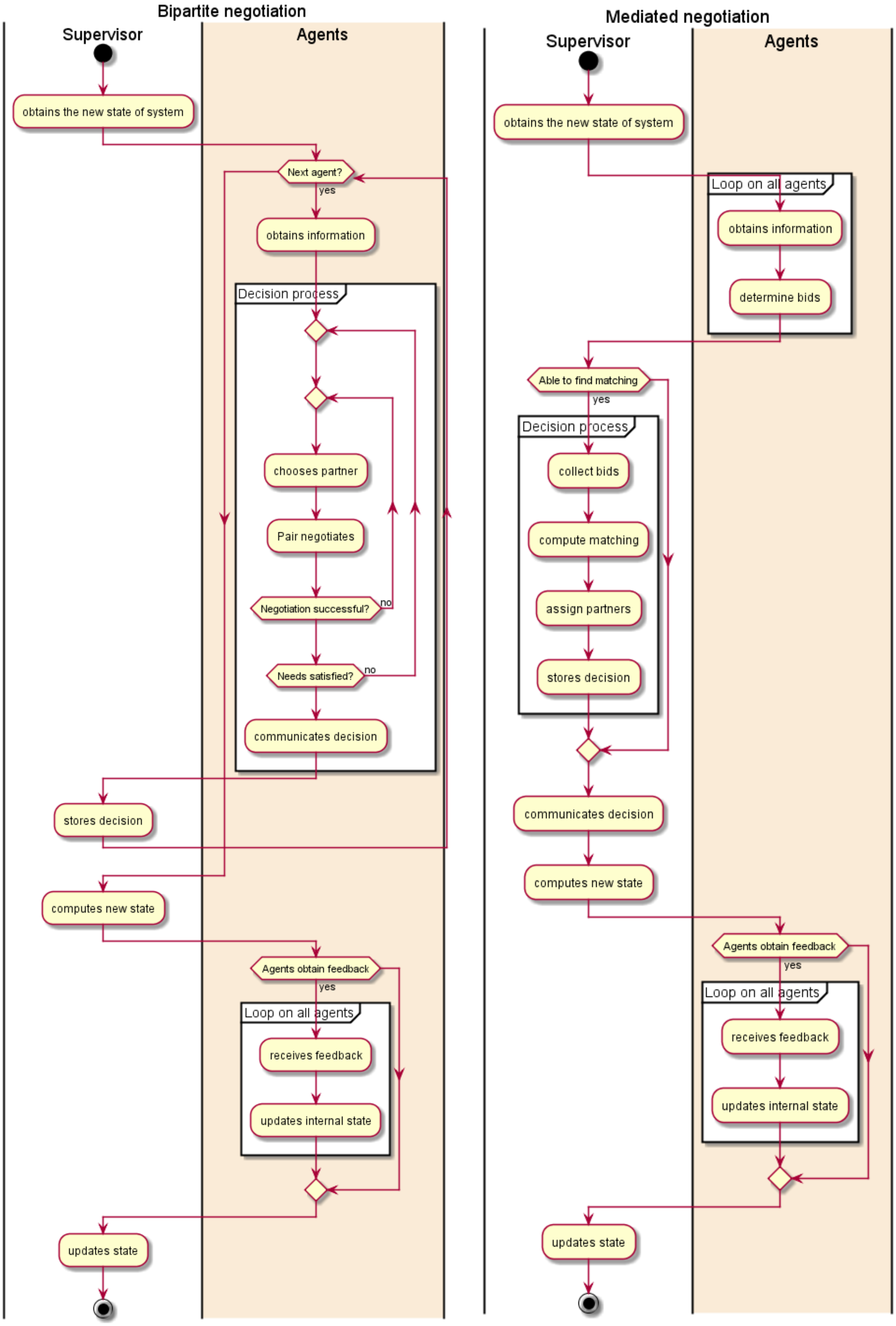
```
self.mu1=kwargs["mu1"], self.s1=1, self.mu2=kwargs["mu2"], self.s2=0.5
self.produce_low = kwargs["buy_low"], self.produce_high = kwargs["buy_high"]
self.biased_low=kwargs["bias_low"], self.biased_high = kwargs["bias_high"]
self.caste=kwargs["low_caste"], self.bias_mediator = kwargs["bias_degree"]
self.tariff_avg = kwargs["tariff_avg"], self.produce_avg = kwargs["produce_avg"]

tariff = data[timestep]["inrpriceperkwh"+str(int(self.tariff_avg))]
tariff_new = abs(np.random.normal(loc=float(tariff),scale=self.s2))
production = self.produce_avg*np.random.uniform(20000,100000)*8/24/20000
ret=[{"consumption":
                int(abs(np.random.normal(loc=self.mu2, scale=self.s1)))
                if i>len(population)*self.caste else
                int(abs(np.random.normal(loc=self.mu1, scale=self.s1))),
        "tariff":tariff_new,
        "social_type": (2 if i>len(population)*self.caste else 1),
        "old_production":0,"old_consumption":0,
        "production":
                (0 if i<len(population)*(1-self.caste)*(1-self.produce_high)
                else(int(abs(np.random.normal(production, self.s2)))
                        if i<len(population)*(1-self.caste)
                        else(0 if i<len(population)*((1-self.caste)+
                        self.caste*(1-self.produce_low))
                                else abs(np.random.normal(production, self.s2))))),
        "biased":
                (0 if i<len(population)*(1-self.caste)*(1-self.biased_high)
                        else(1 if i<len(population)*(1-self.caste)
                                else(0 if i<len(population)*((1-self.caste)
                                +self.caste*(1-self.biased_low))
                                        else 1))),
        "bias_degree":
                (0 if i>len(population)*self.bias_mediator else 1),
        "agentID":0, "main_cost":0.1, "cost":0, "timestep":timestep, "type":None}
        for i in range(len(population))]
        # high class is 2, low class is 1, main_cost is maintenance cost
```

Listing A.4: MeasurementsGenBinomial class

```
ret=[{"production": (np.random.normal(loc=self.mu1, scale=self.s1)
        if i>len(population)*self.caste else np.random.normal(loc=self.mu2, scale=self.s2)),
        "consumption":(np.random.normal(loc=self.mu1, scale=self.s1)
        if i>len(population)*self.caste else np.random.normal(loc=self.mu2, scale=self.s2)),
        "tariff":np.random.uniform(1,5),"main_cost":0.1,
        "social_type":(2 if i>len(population)*self.caste else 1),
        "biased":(0 if i<len(population)*(1-self.caste)*(1-self.biased_high)
        else(1 if i<len(population)*(1-self.caste)
        else(0 if i<len(population)*((1-self.caste)+self.caste*(1-self.biased_low))
        else 1))), "bias_degree":(choice((True,False),1,p=(self.bias_mediator,
                (1-self.bias_mediator))))[0],
        "cost":0,"timestep":timestep,"agentID":0} for i in range(len(population))]
```

Listing A.5: run_experiment function

```
for r in range(conf["reps"]):
        for idx,p in expandgrid(conf["params"]).iterrows():
                params=p.to_dict()
                params.update({"repetition":r})
                f=functools.partial(conf["meas_fct"],**params)
                model=BaseSupervisor(N=int(params["N"]),
                        measurement_fct=f,
                        decision_fct=conf["dec_fct"],
                        agent_decision_fct=conf["dec_fct_agent"],
                        reward_fct=conf["rew_fct"],
                        evaluation_fct=conf["eval_fct"],
                        agent_type=NegoAgent)
                model.run(conf["T"],params=params)
                log_tot=log_tot+model.log
                varnames=[k for k,v in conf["params"].items() if len(v)>1]
                for varname in varnames:
                stats_eval=get_stats(log_tot,
                        "evaluation",idx=[varname],
                        cols=["gini(seller-buyer␣inequality)","efficiency","wealth_distribution"
                stats_all.to_csv("evaluations_"+str(varname)+".csv")
                plot_measures(stats_eval,varname,"./eval_"+str(test)+
                        "_"+str(varname)+"_nego.png")
```



(a) Bilateral model

(b) Mediated model

Figure A.1: Expanded sequence diagrams

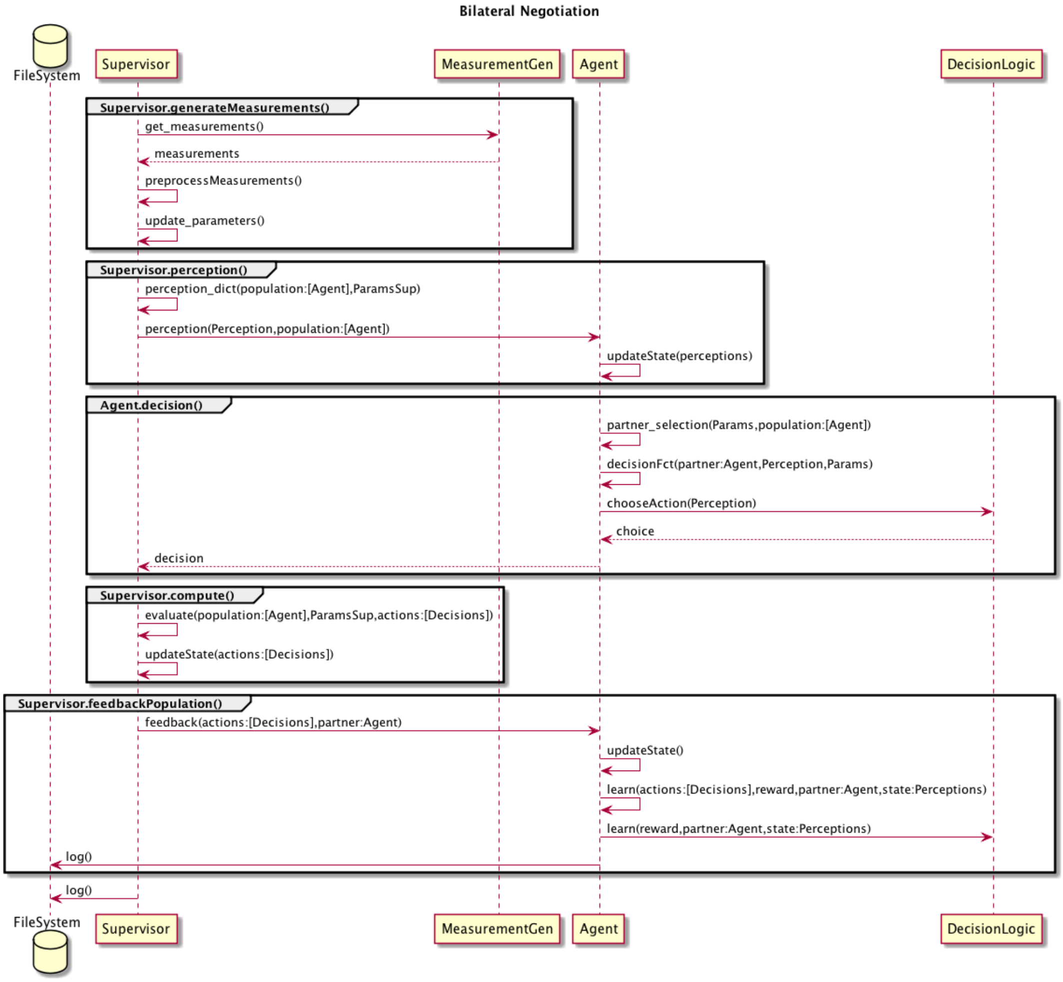


Figure A.2: Sequence diagram: Bilateral model

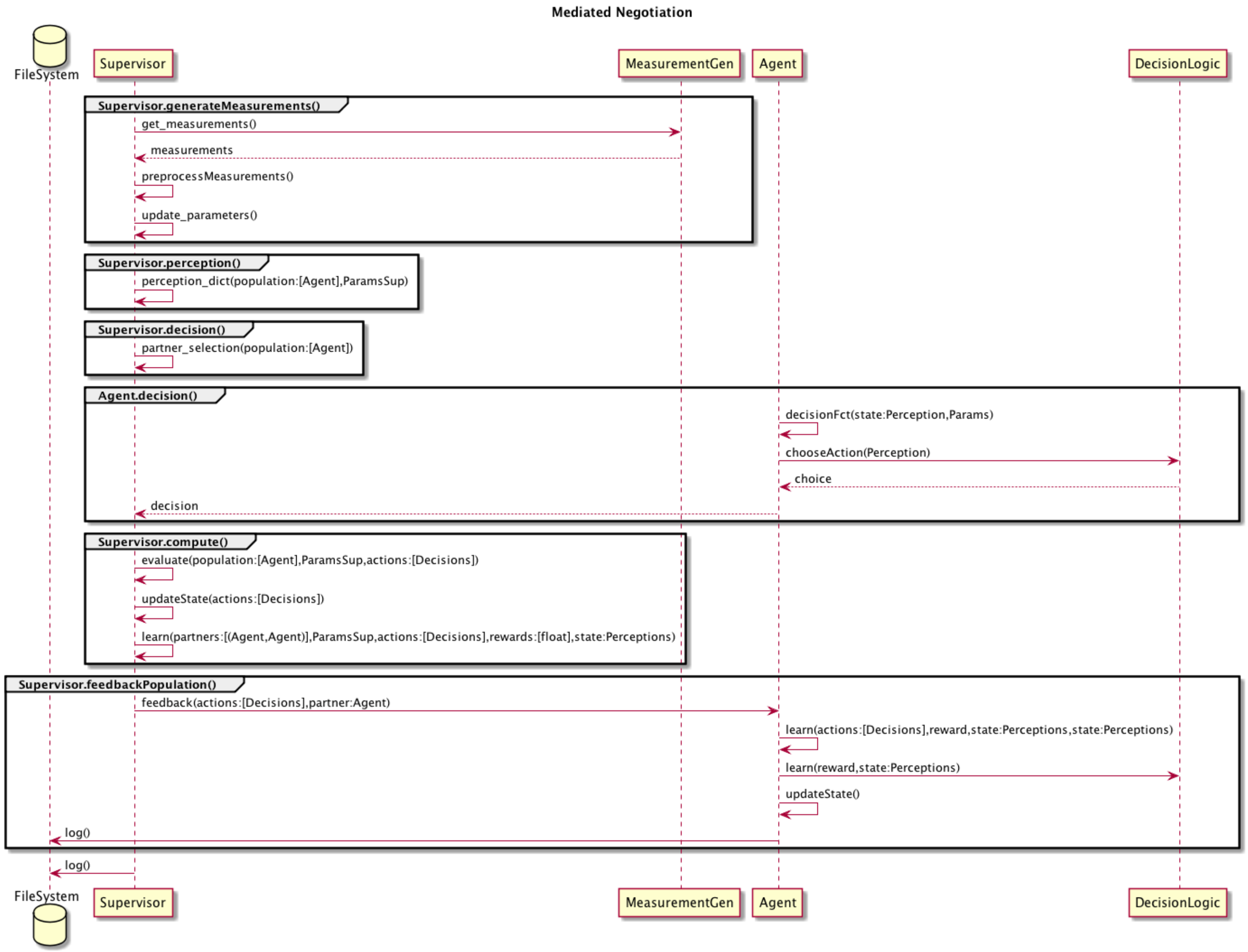


Figure A.3: Sequence diagram: Mediated model

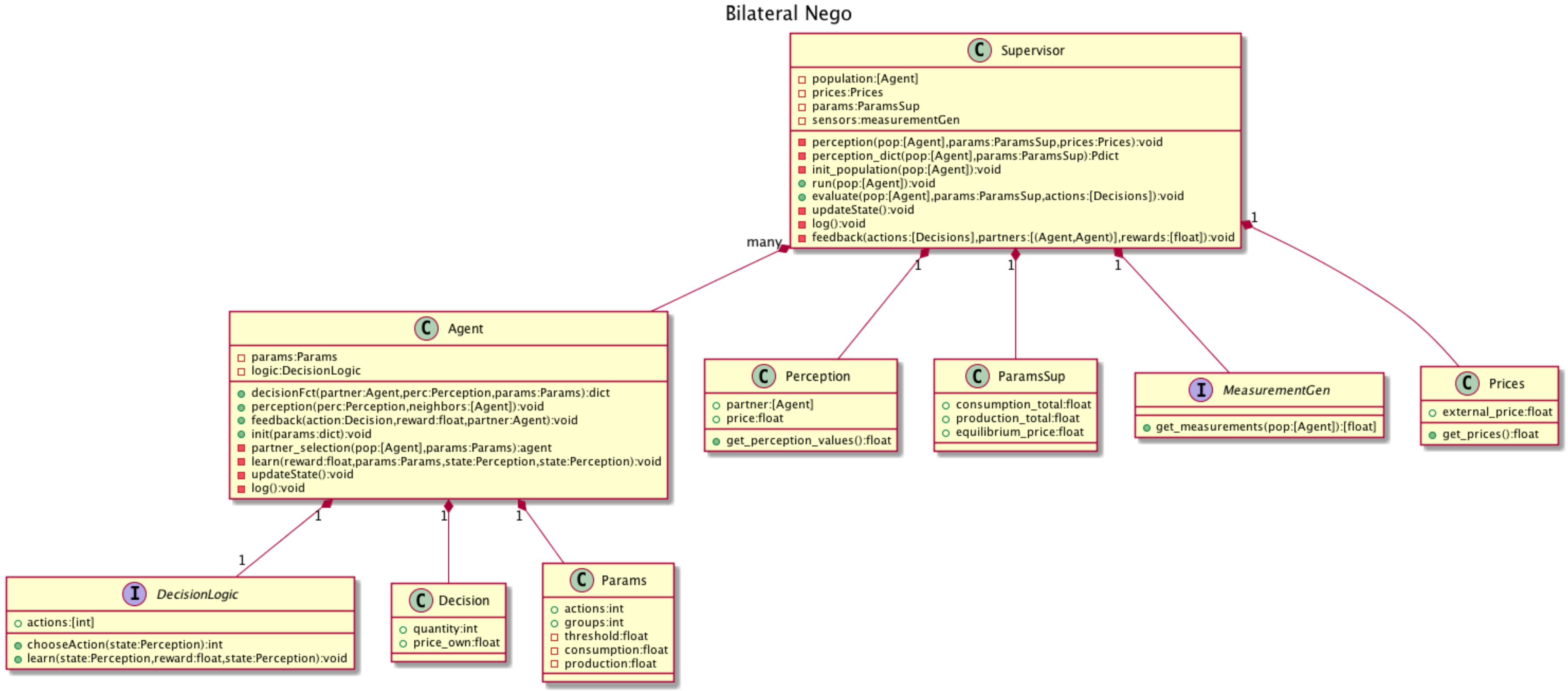


Figure A.4: Class diagram: Bilateral model

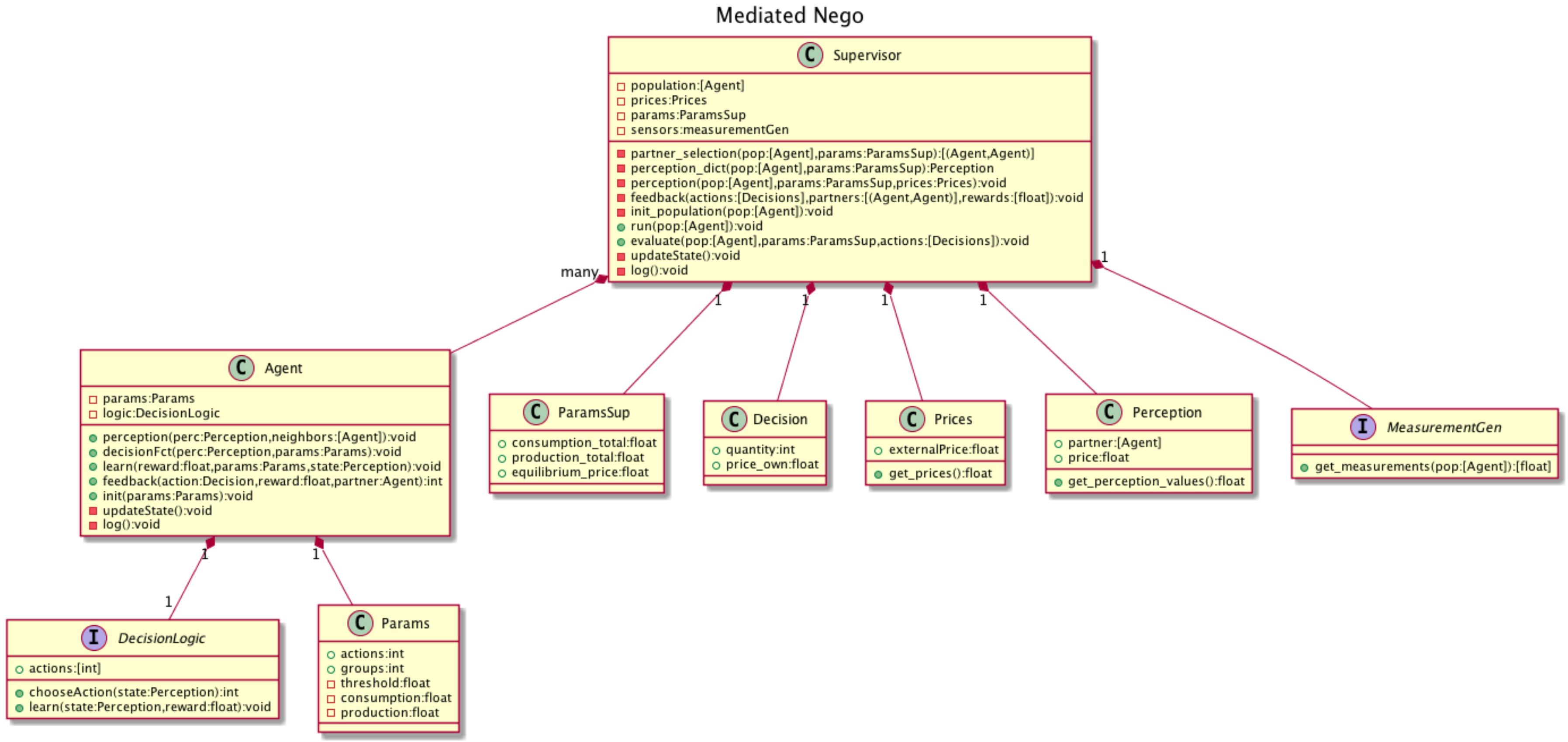


Figure A.5: Class diagram: Mediated model

Table A.1: Dataset for load profile

	Dataset 1 [1]	Dataset 2 [2]	Dataset 3 [3]	Dataset 4 [4]	Dataset 5 [5]
Region	USA state level	USA	UK	Germany	USA
Year	2013	2005	1997	2013	2014-2016
Duration of recording	hourly load profile data	year	half-hourly	year	15 minutes
Total Duration	year	year	year	year	3 years
Type	Average consumptions: Base, High, Low	Average consumptions and expenditures	Average consumption	Total consumption	Total consumption
Dependent parameters	Time	household size, income category, race and age.	Profile, Time	Time	443 houses : Household and season
Consumption values	Heating, Cooling, Fan, Lights, equipments	Total	Avergae	Total	Total

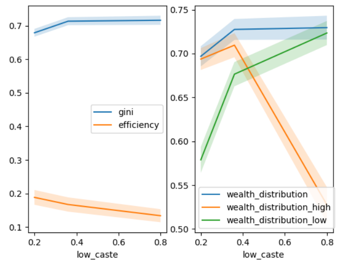
[1] https://openei.org/datasets/dataset/commercial-and-residential-hourly-load-profiles-for-all-tmy3-locations-in-the-united-states

[2] https://openei.org/datasets/dataset/residential-energy-consumption-survey-results-total-energy-consumption-expenditures-and-intensiti

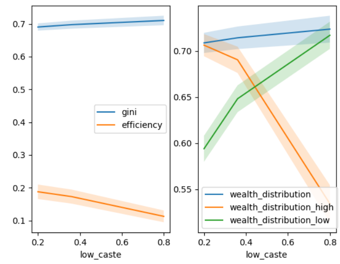
[3] http://ukerc.rl.ac.uk/DC/cgi-bin/edc_search.pl?GoButton=Detail&WantComp=42&WantResult=&WantText=EDC0000041

[4] https://open-power-system-data.org/data-sources#11_European_load_data

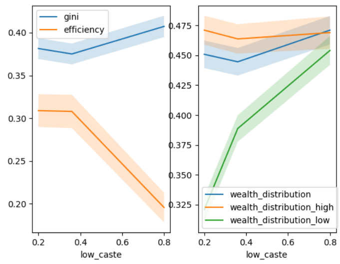
[5] http://traces.cs.umass.edu/index.php/Smart/Smart



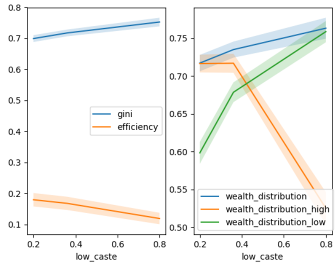
(a) Bilateral



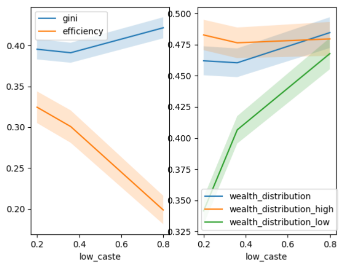
(b) Mediated



(c) Mediated bid split

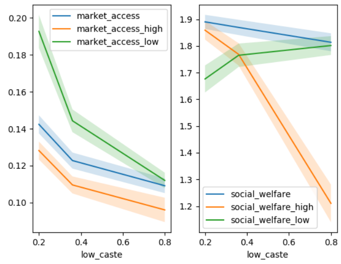


(d) Mediated discrimination

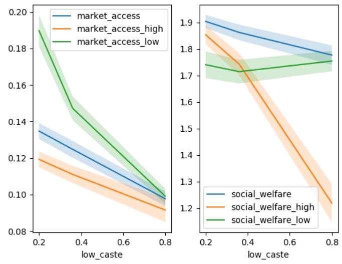


(e) Mediated bid split discrimination

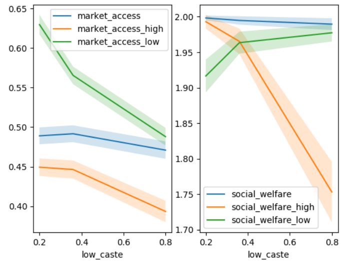
Figure A.6: Gini(seller-buyer inequality), Efficiency and wealth distribution(wealth inequality) with low caste proportion variation



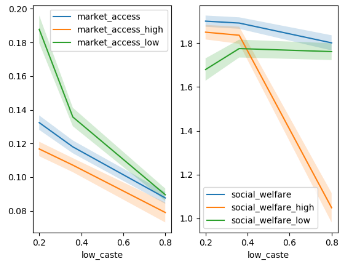
(a) Bilateral



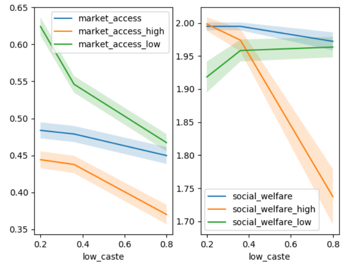
(b) Mediated



(c) Mediated bid split

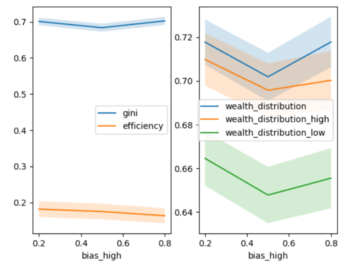


(d) Mediated discrimination

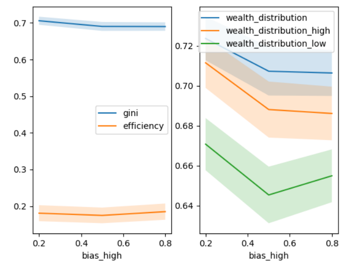


(e) Mediated bid split discrimination

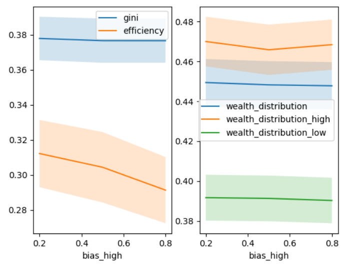
Figure A.7: Market access and social welfare with low caste proportion variation



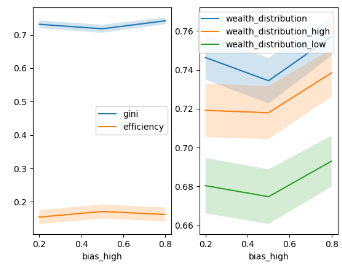
(a) Bilateral



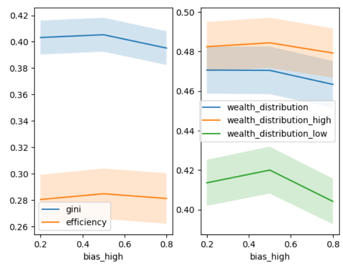
(b) Mediated



(c) Mediated bid split

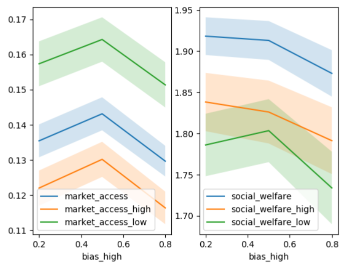


(d) Mediated discrimination

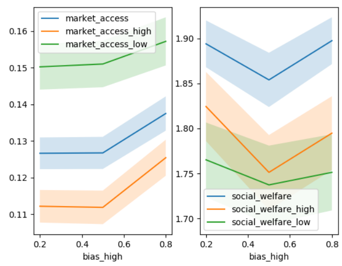


(e) Mediated bid split discrimination

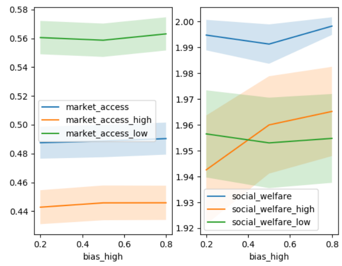
Figure A.8: Gini(seller-buyer inequality), Efficiency and wealth distribution(wealth inequality) with bias high proportion variation



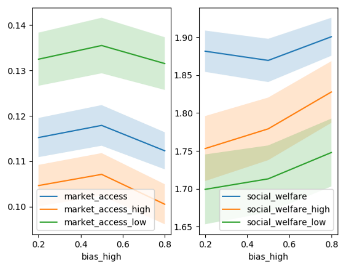
(a) Bilateral



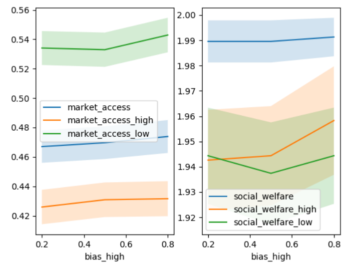
(b) Mediated



(c) Mediated bid split

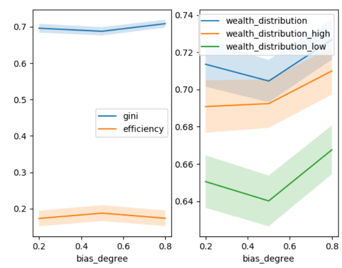


(d) Mediated discrimination

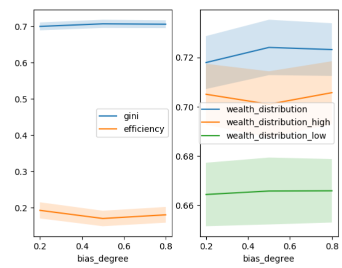


(e) Mediated bid split discrimination

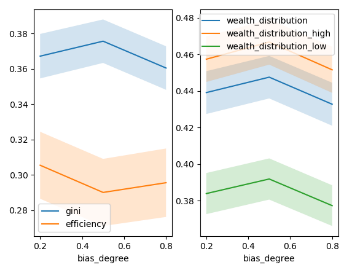
Figure A.9: Market access and social welfare with bias high proportion variation



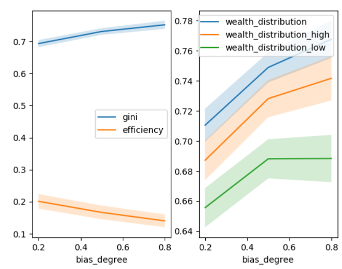
(a) Bilateral



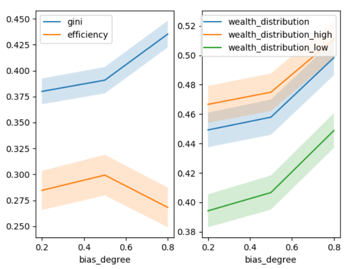
(b) Mediated



(c) Mediated bid split

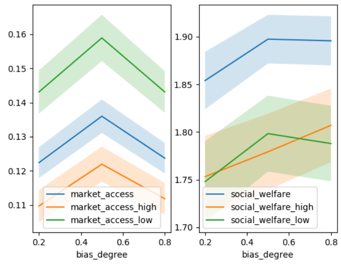


(d) Mediated discrimination

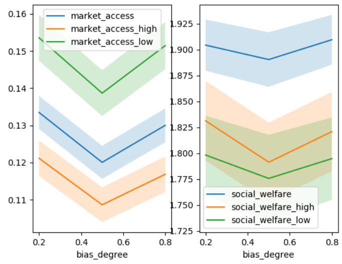


(e) Mediated bid split discrimination

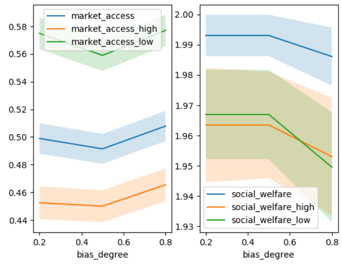
Figure A.10: Gini(seller-buyer inequality), Efficiency and wealth distribution(wealth inequality) with bias degree variation



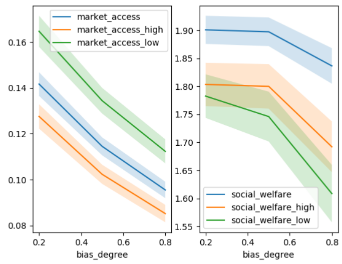
(a) Bilateral



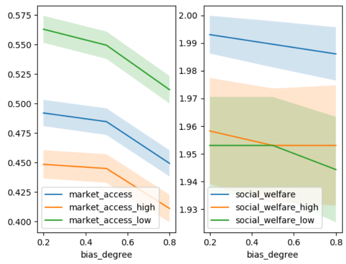
(b) Mediated



(c) Mediated bid split

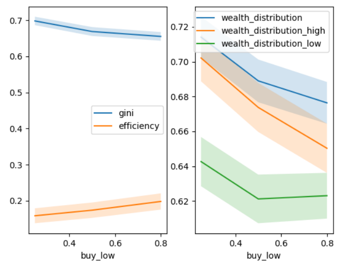


(d) Mediated discrimination

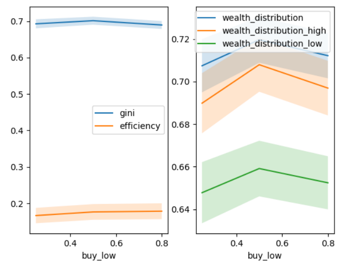


(e) Mediated bid split discrimination

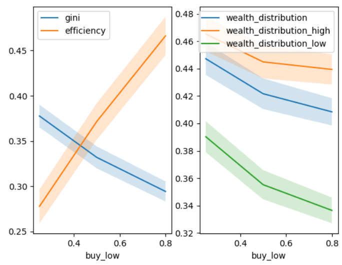
Figure A.11: Market access and social welfare with bias degree variation



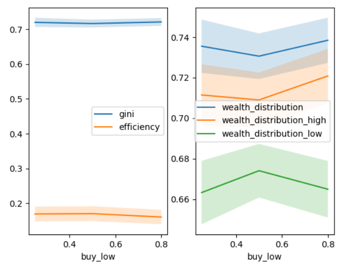
(a) Bilateral



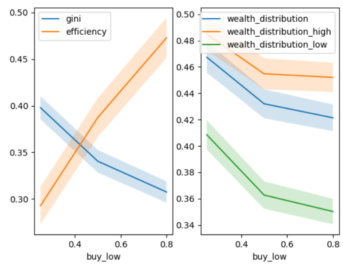
(b) Mediated



(c) Mediated bid split

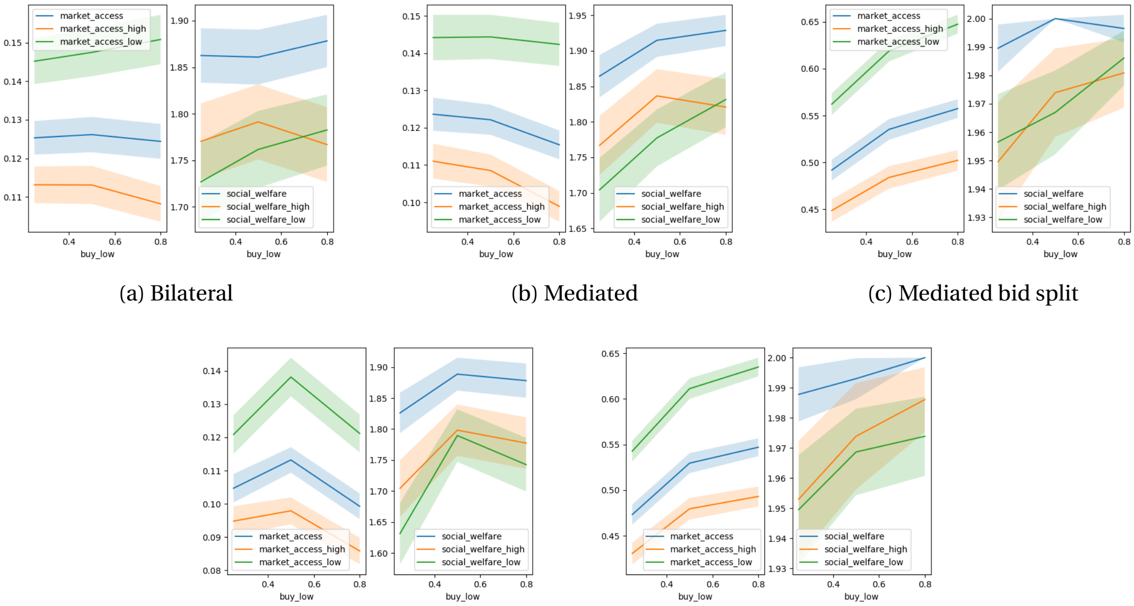


(d) Mediated discrimination



(e) Mediated bid split discrimination

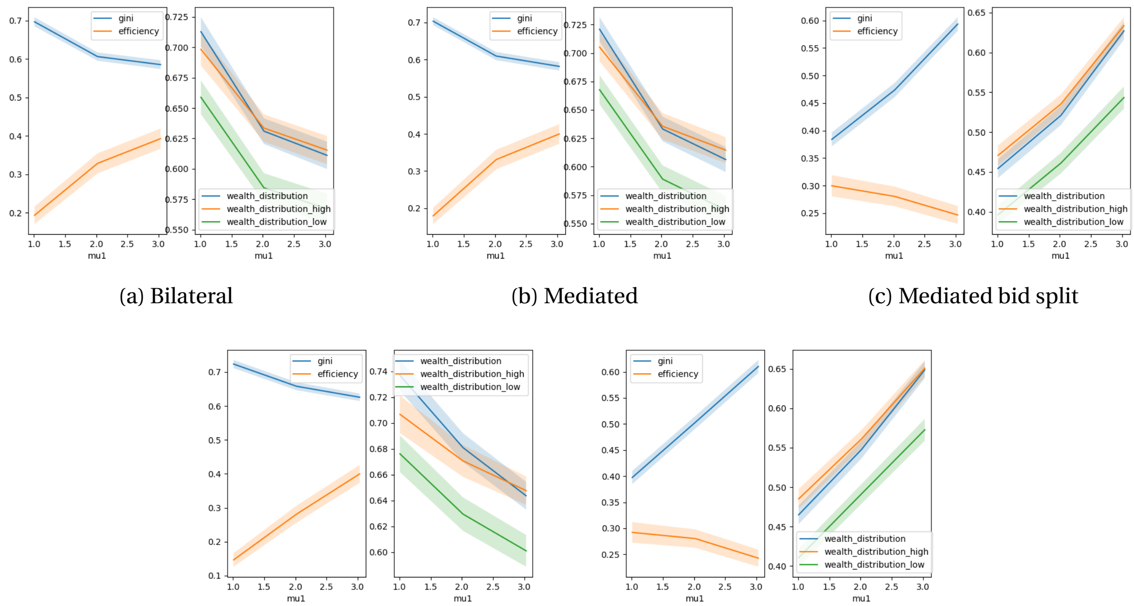
Figure A.12: Gini(seller-buyer inequality), Efficiency and wealth distribution(wealth inequality) with buy low variation



(a) Bilateral (b) Mediated (c) Mediated bid split

(d) Mediated discrimination (e) Mediated bid split discrimination

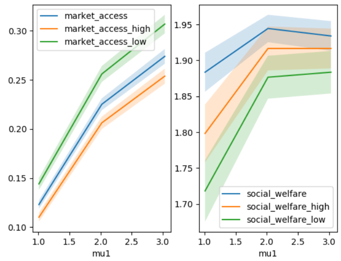
Figure A.13: Market access and social welfare with buy low variation



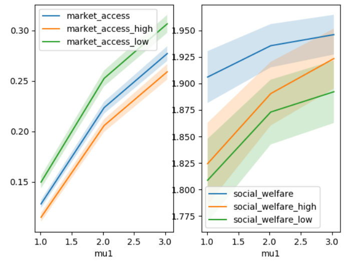
(a) Bilateral (b) Mediated (c) Mediated bid split

(d) Mediated discrimination (e) Mediated bid split discrimination

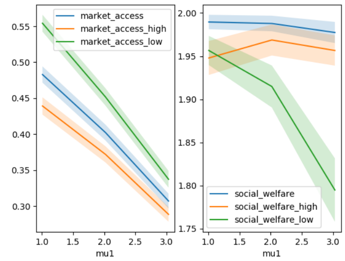
Figure A.14: Gini(seller-buyer inequality), Efficiency and wealth distribution(wealth inequality) with consumption for low caste variation



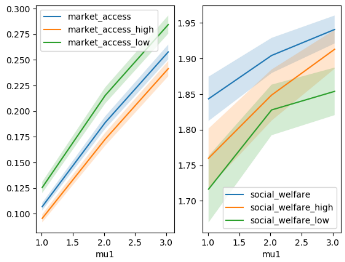
(a) Bilateral



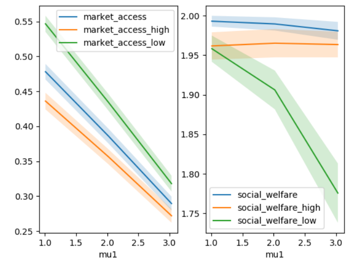
(b) Mediated



(c) Mediated bid split

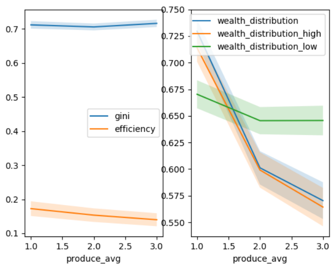


(d) Mediated discrimination

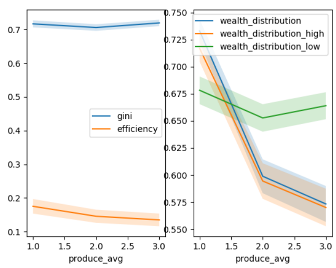


(e) Mediated bid split discrimination

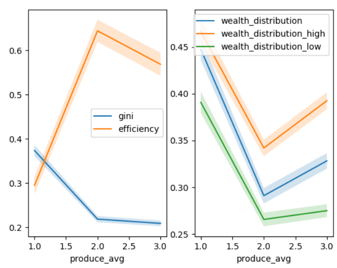
Figure A.15: Market access and social welfare with consumption for low caste variation



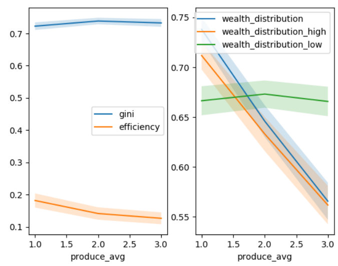
(a) Bilateral



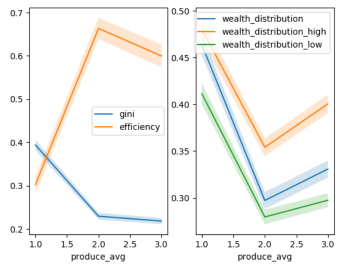
(b) Mediated



(c) Mediated bid split

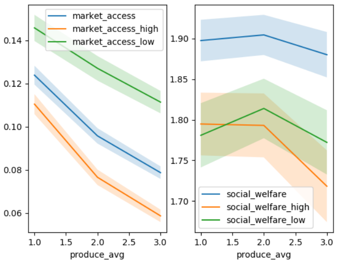


(d) Mediated discrimination

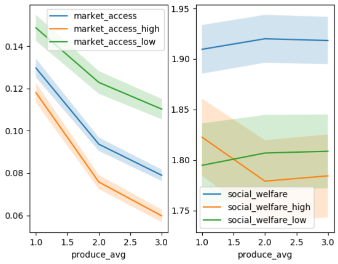


(e) Mediated bid split discrimination

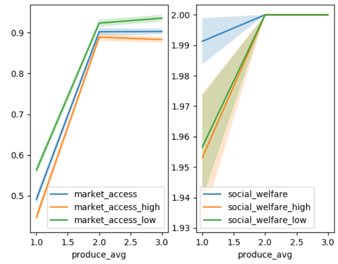
Figure A.16: Gini(seller-buyer inequality), Efficiency and wealth distribution(wealth inequality) with production variation



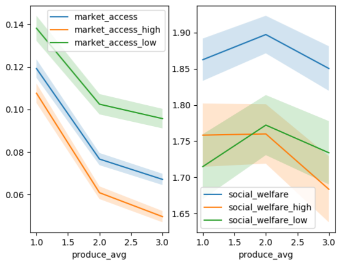
(a) Bilateral



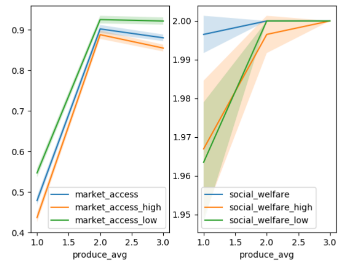
(b) Mediated



(c) Mediated bid split

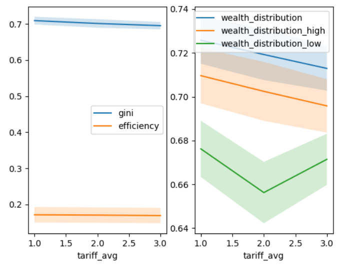


(d) Mediated discrimination

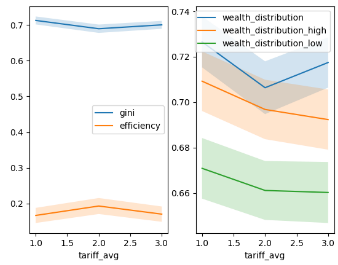


(e) Mediated bid split discrimination

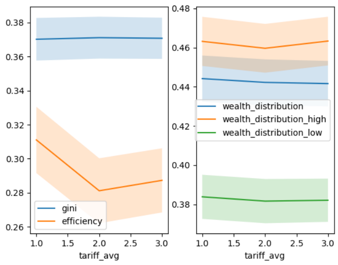
Figure A.17: Market access and social welfare with production variation



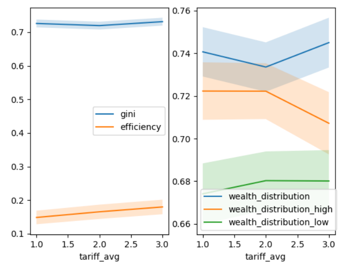
(a) Bilateral



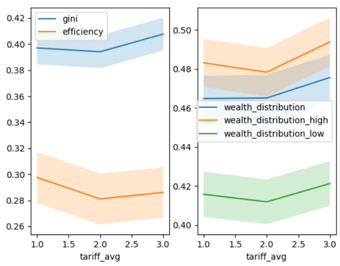
(b) Mediated



(c) Mediated bid split

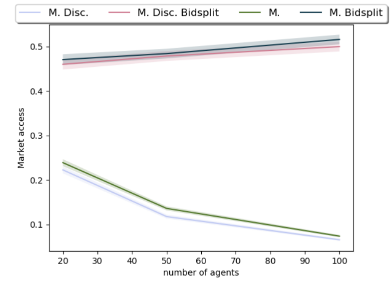


(d) Mediated discrimination

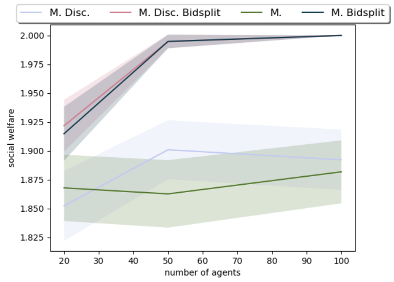


(e) Mediated bid split discrimination

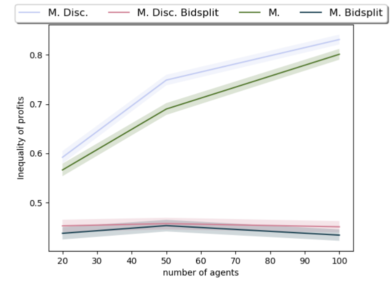
Figure A.18: Gini(seller-buyer inequality), Efficiency and wealth distribution(wealth inequality) with tariff variation



(a) Market access

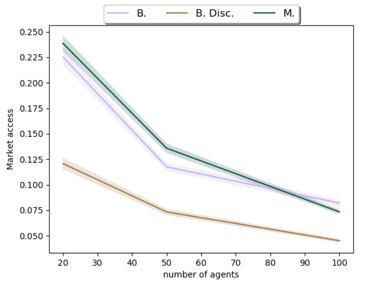


(b) Social welfare

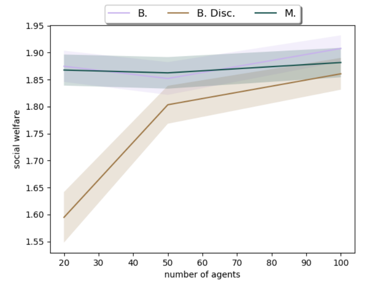


(c) wealth distribution

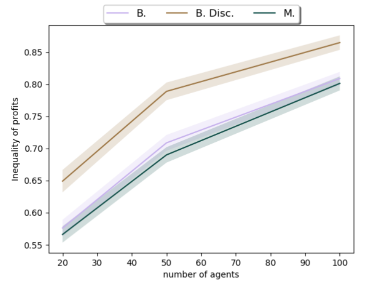
Figure A.19: All mediation evaluation comparisons



(a) Market access

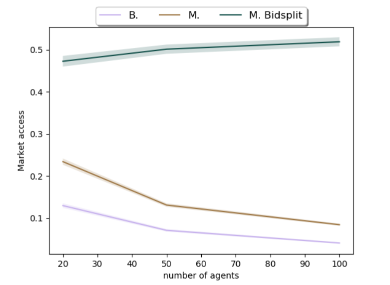


(b) Social welfare

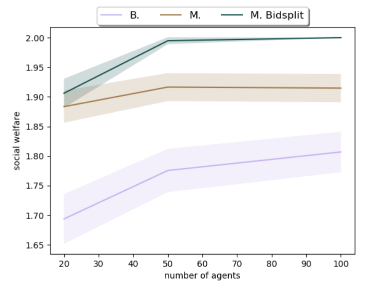


(c) wealth distribution

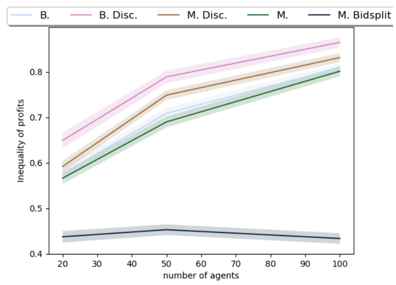
Figure A.20: Mediation versus base evaluation comparisons



(a) Market access

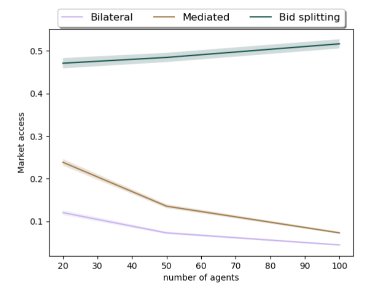


(b) Social welfare

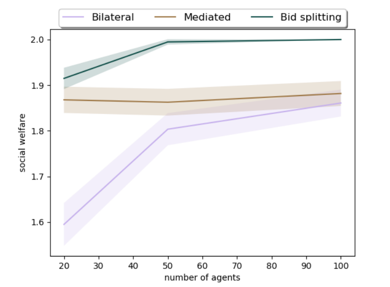


(c) wealth distribution

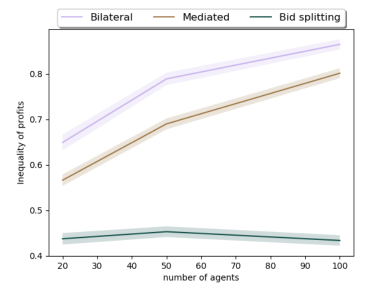
Figure A.21: Bidsplit versus base evaluation comparisons



(a) Market access



(b) Social welfare



(c) wealth distribution

Figure A.22: All evaluation comparisons

Table A.2: Comparison of experiments(1) showing mean values of g: gini(seller-buyer inequality), e: efficiency w(h/l): wealth distribution(wealth inequality)(high/low caste), sw(h/l): social welfare(high/low), ma(h/l):market access(high/low)

parameter-value	exp	g	e	w	wh	wl	sw	swh	swl	ma	mah	mal
tariff 1	base	0.77	0.12	0.78	0.75	0.70	1.79	1.66	1.53	0.08	0.07	0.09
	exp1	0.71	0.17	0.73	0.71	0.67	1.89	1.77	1.75	0.12	0.11	0.14
	exp2	0.37	0.31	0.44	0.46	0.38	1.99	1.96	1.96	0.50	0.45	0.57
	exp3	0.73	0.15	0.74	0.72	0.67	1.88	1.77	1.69	0.12	0.11	0.14
	exp4	0.40	0.30	0.46	0.48	0.42	2.00	1.96	1.96	0.48	0.44	0.55
tariff 2	base	0.78	0.11	0.79	0.77	0.70	1.81	1.68	1.53	0.08	0.07	0.09
	exp1	0.69	0.19	0.71	0.70	0.66	1.89	1.81	1.81	0.13	0.12	0.15
	exp2	0.37	0.28	0.44	0.46	0.38	1.98	1.94	1.95	0.49	0.45	0.57
	exp3	0.72	0.17	0.73	0.72	0.68	1.89	1.82	1.77	0.11	0.10	0.13
	exp4	0.39	0.28	0.47	0.48	0.41	1.99	1.95	1.94	0.47	0.43	0.54
tariff 3	base	0.77	0.12	0.78	0.74	0.69	1.77	1.62	1.43	0.07	0.07	0.08
	exp1	0.70	0.17	0.72	0.69	0.66	1.88	1.79	1.77	0.12	0.11	0.14
	exp2	0.37	0.29	0.44	0.46	0.38	1.99	1.95	1.95	0.50	0.46	0.57
	exp3	0.73	0.18	0.75	0.71	0.68	1.87	1.75	1.68	0.12	0.11	0.13
	exp4	0.41	0.29	0.48	0.49	0.42	1.99	1.95	1.96	0.46	0.42	0.53
produce 1	base	0.78	0.11	0.80	0.75	0.68	1.77	1.61	1.39	0.07	0.06	0.08
	exp1	0.72	0.18	0.73	0.72	0.68	1.91	1.82	1.79	0.13	0.12	0.15
	exp2	0.37	0.29	0.45	0.47	0.39	1.99	1.95	1.96	0.49	0.45	0.56
	exp3	0.72	0.18	0.74	0.71	0.67	1.86	1.76	1.71	0.12	0.11	0.14
	exp4	0.39	0.30	0.46	0.48	0.41	2.00	1.97	1.96	0.48	0.44	0.55
produce 2	base	0.76	0.11	0.64	0.62	0.68	1.81	1.63	1.67	0.06	0.05	0.08
	exp1	0.71	0.15	0.60	0.59	0.65	1.92	1.78	1.81	0.09	0.08	0.12
	exp2	0.22	0.64	0.29	0.34	0.27	2.00	2.00	2.00	0.90	0.89	0.92
	exp3	0.74	0.14	0.65	0.63	0.67	1.90	1.76	1.77	0.08	0.06	0.10
	exp4	0.23	0.66	0.30	0.35	0.28	2.00	2.00	2.00	0.90	0.89	0.92
produce 3	base	0.74	0.12	0.57	0.55	0.66	1.74	1.55	1.54	0.05	0.04	0.07
	exp1	0.72	0.13	0.57	0.57	0.66	1.92	1.78	1.81	0.08	0.06	0.11
	exp2	0.21	0.57	0.33	0.39	0.27	2.00	2.00	2.00	0.90	0.88	0.94
	exp3	0.73	0.13	0.57	0.56	0.67	1.85	1.68	1.73	0.07	0.05	0.10
	exp4	0.22	0.60	0.33	0.40	0.30	2.00	2.00	2.00	0.88	0.85	0.92
N 20	base	0.62	0.09	0.65	0.60	0.51	1.59	1.39	1.14	0.12	0.11	0.14
	exp1	0.54	0.13	0.57	0.55	0.48	1.87	1.76	1.69	0.24	0.22	0.26
	exp2	0.37	0.11	0.44	0.44	0.34	1.91	1.87	1.79	0.47	0.44	0.52
	exp3	0.57	0.15	0.59	0.57	0.51	1.85	1.77	1.64	0.22	0.21	0.24
	exp4	0.38	0.11	0.45	0.46	0.36	1.92	1.86	1.81	0.46	0.43	0.51
N 50	base	0.78	0.11	0.79	0.76	0.71	1.80	1.65	1.54	0.07	0.07	0.08
	exp1	0.67	0.18	0.69	0.68	0.65	1.86	1.78	1.81	0.14	0.12	0.16
	exp2	0.38	0.28	0.45	0.47	0.40	1.99	1.95	1.96	0.48	0.44	0.55
	exp3	0.74	0.16	0.75	0.73	0.68	1.90	1.81	1.73	0.12	0.11	0.14
	exp4	0.39	0.28	0.46	0.47	0.40	1.99	1.97	1.96	0.48	0.44	0.55
N 100	base	0.86	0.12	0.86	0.82	0.79	1.86	1.69	1.59	0.05	0.04	0.05
	exp1	0.79	0.17	0.80	0.78	0.75	1.88	1.81	1.84	0.07	0.07	0.09
	exp2	0.36	0.54	0.43	0.46	0.38	2.00	1.99	1.99	0.52	0.48	0.59
	exp3	0.82	0.15	0.83	0.81	0.78	1.89	1.79	1.79	0.07	0.06	0.08
	exp4	0.38	0.54	0.45	0.47	0.40	2.00	1.99	1.99	0.50	0.46	0.56

Table A.3: Comparison of experiments(2)

parameter-value	**exp**	**g**	**e**	**w**	**wh**	**wl**	**sw**	**swh**	**swl**	**ma**	**mah**	**mal**
mu1 1.01	base	0.77	0.10	0.78	0.75	0.68	1.76	1.56	1.43	0.07	0.06	0.08
	exp1	0.70	0.18	0.72	0.71	0.67	1.91	1.82	1.81	0.13	0.12	0.15
	exp2	0.38	0.30	0.45	0.47	0.40	1.99	1.95	1.96	0.48	0.44	0.55
	exp3	0.72	0.15	0.74	0.71	0.68	1.84	1.76	1.72	0.11	0.10	0.13
	exp4	0.40	0.29	0.46	0.49	0.41	1.99	1.96	1.96	0.48	0.44	0.55
mu1 2.02	base	0.74	0.23	0.76	0.75	0.69	1.87	1.78	1.63	0.13	0.12	0.15
	exp1	0.61	0.33	0.63	0.64	0.59	1.94	1.89	1.87	0.22	0.21	0.25
	exp2	0.47	0.28	0.52	0.54	0.46	1.99	1.97	1.91	0.40	0.37	0.45
	exp3	0.66	0.28	0.68	0.67	0.63	1.90	1.85	1.83	0.19	0.17	0.22
	exp4	0.50	0.28	0.55	0.56	0.49	1.99	1.97	1.91	0.39	0.36	0.43
mu1 3.03	base	0.74	0.30	0.76	0.75	0.69	1.91	1.85	1.69	0.15	0.14	0.17
	exp1	0.58	0.40	0.61	0.61	0.56	1.95	1.92	1.89	0.28	0.26	0.31
	exp2	0.59	0.25	0.63	0.63	0.54	1.98	1.96	1.79	0.31	0.29	0.34
	exp3	0.63	0.40	0.64	0.65	0.60	1.94	1.91	1.85	0.26	0.24	0.28
	exp4	0.61	0.24	0.65	0.65	0.57	1.98	1.96	1.78	0.29	0.27	0.32
low caste 20	base	0.78	0.13	0.79	0.77	0.64	1.82	1.72	1.27	0.08	0.07	0.11
	exp1	0.69	0.19	0.71	0.71	0.59	1.90	1.85	1.74	0.13	0.12	0.19
	exp2	0.38	0.31	0.45	0.47	0.32	2.00	1.99	1.92	0.49	0.45	0.63
	exp3	0.70	0.18	0.72	0.72	0.60	1.90	1.85	1.68	0.13	0.12	0.19
	exp4	0.40	0.32	0.46	0.48	0.34	1.99	2.00	1.92	0.48	0.44	0.62
low caste 36	base	0.79	0.12	0.81	0.78	0.71	1.83	1.67	1.53	0.08	0.07	0.10
	exp1	0.70	0.17	0.71	0.69	0.65	1.86	1.74	1.71	0.12	0.11	0.15
	exp2	0.38	0.31	0.44	0.46	0.39	1.99	1.97	1.96	0.49	0.45	0.57
	exp3	0.72	0.17	0.73	0.72	0.68	1.89	1.84	1.78	0.12	0.11	0.14
	exp4	0.39	0.30	0.46	0.48	0.41	1.99	1.97	1.96	0.48	0.44	0.55
low caste 80	base	0.79	0.08	0.80	0.49	0.79	1.74	0.72	1.68	0.06	0.06	0.06
	exp1	0.71	0.11	0.72	0.53	0.72	1.78	1.22	1.75	0.10	0.09	0.10
	exp2	0.41	0.20	0.47	0.47	0.45	1.99	1.75	1.98	0.47	0.39	0.49
	exp3	0.75	0.12	0.76	0.53	0.76	1.80	1.05	1.76	0.09	0.08	0.09
	exp4	0.42	0.20	0.48	0.48	0.47	1.97	1.74	1.96	0.45	0.37	0.47
buy low 20	base	0.78	0.12	0.80	0.77	0.71	1.83	1.69	1.56	0.08	0.07	0.09
	exp1	0.69	0.17	0.71	0.69	0.65	1.86	1.77	1.70	0.12	0.11	0.14
	exp2	0.38	0.28	0.45	0.47	0.39	1.99	1.95	1.96	0.49	0.45	0.56
	exp3	0.72	0.17	0.74	0.71	0.66	1.83	1.70	1.63	0.10	0.09	0.12
	exp4	0.40	0.29	0.47	0.48	0.41	1.99	1.95	1.95	0.47	0.43	0.54
buy low 50	base	0.77	0.14	0.78	0.75	0.71	1.81	1.65	1.53	0.07	0.06	0.09
	exp1	0.70	0.18	0.72	0.71	0.66	1.91	1.84	1.78	0.12	0.11	0.14
	exp2	0.33	0.37	0.42	0.44	0.36	2.00	1.97	1.97	0.54	0.48	0.62
	exp3	0.72	0.17	0.73	0.71	0.67	1.89	1.80	1.79	0.11	0.10	0.14
	exp4	0.34	0.39	0.43	0.45	0.36	1.99	1.97	1.97	0.53	0.48	0.61
buy low 80	base	0.75	0.15	0.76	0.74	0.69	1.81	1.68	1.60	0.08	0.07	0.09
	exp1	0.69	0.18	0.71	0.70	0.65	1.93	1.82	1.83	0.12	0.10	0.14
	exp2	0.29	0.47	0.41	0.44	0.34	2.00	1.98	1.99	0.56	0.50	0.65
	exp3	0.72	0.16	0.74	0.72	0.66	1.88	1.78	1.74	0.10	0.09	0.12
	exp4	0.31	0.47	0.42	0.45	0.35	2.00	1.99	1.97	0.55	0.49	0.63

Table A.4: Comparison of experiments(3)

parameter-value	exp	g	e	w	wh	wl	sw	swh	swl	ma	mah	mal
bias high 20	base	0.75	0.11	0.77	0.73	0.67	1.72	1.56	1.38	0.07	0.06	0.08
	exp1	0.71	0.18	0.72	0.71	0.67	1.89	1.82	1.77	0.13	0.11	0.15
	exp2	0.38	0.31	0.45	0.47	0.39	1.99	1.94	1.96	0.49	0.44	0.56
	exp3	0.73	0.15	0.75	0.72	0.68	1.88	1.75	1.70	0.12	0.10	0.13
	exp4	0.40	0.28	0.47	0.48	0.41	1.99	1.94	1.94	0.47	0.43	0.53
bias high 50	base	0.77	0.13	0.78	0.74	0.69	1.79	1.65	1.51	0.08	0.07	0.09
	exp1	0.69	0.17	0.71	0.69	0.65	1.85	1.75	1.74	0.13	0.11	0.15
	exp2	0.38	0.30	0.45	0.47	0.39	1.99	1.96	1.95	0.49	0.45	0.56
	exp3	0.72	0.17	0.73	0.72	0.67	1.87	1.78	1.71	0.12	0.11	0.14
	exp4	0.41	0.28	0.47	0.48	0.42	1.99	1.94	1.94	0.47	0.43	0.53
bias high 80	base	0.75	0.11	0.77	0.74	0.67	1.74	1.58	1.41	0.07	0.06	0.08
	exp1	0.69	0.18	0.71	0.69	0.65	1.90	1.79	1.75	0.14	0.13	0.16
	exp2	0.38	0.29	0.45	0.47	0.39	2.00	1.97	1.95	0.49	0.45	0.56
	exp3	0.74	0.16	0.76	0.74	0.69	1.90	1.83	1.75	0.11	0.10	0.13
	exp4	0.40	0.28	0.46	0.48	0.40	1.99	1.96	1.94	0.47	0.43	0.54
bias degree 20	base	0.78	0.13	0.80	0.76	0.71	1.82	1.64	1.52	0.08	0.07	0.09
	exp1	0.70	0.19	0.72	0.71	0.66	1.90	1.83	1.80	0.13	0.12	0.15
	exp2	0.37	0.31	0.44	0.46	0.38	1.99	1.96	1.97	0.50	0.45	0.57
	exp3	0.69	0.20	0.71	0.69	0.66	1.90	1.80	1.78	0.14	0.13	0.16
	exp4	0.38	0.28	0.45	0.47	0.39	1.99	1.96	1.95	0.49	0.45	0.56
bias degree 50	base	0.77	0.11	0.79	0.76	0.69	1.78	1.63	1.47	0.08	0.07	0.09
	exp1	0.71	0.17	0.72	0.70	0.67	1.89	1.79	1.78	0.12	0.11	0.14
	exp2	0.38	0.29	0.45	0.47	0.39	1.99	1.96	1.97	0.49	0.45	0.56
	exp3	0.73	0.17	0.75	0.73	0.69	1.90	1.80	1.75	0.11	0.10	0.13
	exp4	0.39	0.30	0.46	0.47	0.41	1.99	1.95	1.95	0.48	0.44	0.55
bias degree 80	base	0.73	0.11	0.75	0.72	0.67	1.71	1.60	1.45	0.08	0.07	0.09
	exp1	0.71	0.18	0.72	0.71	0.67	1.91	1.82	1.79	0.13	0.12	0.15
	exp2	0.36	0.30	0.43	0.45	0.38	1.99	1.95	1.95	0.51	0.47	0.58
	exp3	0.75	0.14	0.77	0.74	0.69	1.84	1.69	1.61	0.10	0.09	0.11
	exp4	0.44	0.27	0.50	0.51	0.45	1.99	1.95	1.94	0.45	0.41	0.51

Table A.5: ANOVA results to compare different experiments

ANOVA p-values	bias degree	bias high	buy low	low caste
efficiency	5.9E-05	3.9E-08	3.3E-10	3.4E-07
gini	2.3E-72	1.7E-72	2.2E-84	1.4E-62
market_access	2.9E-159	3.8E-183	4.7E-176	1.4E-175
market_access_high	4.8E-131	1.3E-152	4.6E-142	4.3E-131
market_access_low	8.7E-168	2.8E-189	3.1E-188	4.0E-166
social_welfare	7.6E-08	6.9E-13	3.3E-03	8.3E-09
social_welfare_high	7.5E-07	4.6E-11	5.4E-04	1.4E-17
social_welfare_low	3.6E-10	1.2E-13	1.4E-05	2.2E-15
wealth_distribution	1.5E-65	3.1E-57	1.8E-71	1.66E-50
wealth_distribution_high	2.9E-41	2.3E-30	1.1E-40	3.46E-12
wealth_distribution_low	1.8E-41	1.3E-35	1.2E-49	2.64E-36

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