Learnable Strategies for Bilateral Agent Negotiation over Multiple Issues

Pallavi Bagga\textsuperscript{1}, Nicola Paoletti\textsuperscript{2}, Kostas Stathis\textsuperscript{3}
Royal Holloway, University of London, UK
\{pallavi.bagga.2017\textsuperscript{1}, nicola.paoletti\textsuperscript{2}, kostas.stathis\textsuperscript{3}\}@rhul.ac.uk

Abstract
We present a novel bilateral agent negotiation model supporting multiple issues under user preference uncertainty. This model relies upon interpretable strategy templates representing agent negotiation tactics with learnable parameters. It also uses deep reinforcement learning to evaluate threshold utilities for those tactics that require them. To handle user preference uncertainty, our approach uses stochastic search to derive the user model that best approximates a given partial preference profile. Multi-objective optimization and multi-criteria decision-making methods are applied at negotiation time to generate near Pareto-optimal bids. We empirically show that our agent model outperforms winning agents of previous automated negotiation competitions in terms of the individual as well as social-welfare utilities. Also, the adaptive nature of our learning-based agent model provides a significant advantage when our agent confronts unknown opponents in unseen negotiation scenarios.

Introduction
An important problem in multi-issue bilateral negotiation is how to model a self-interested agent learn to adapt its strategy while negotiating with other agents. A model of this kind mostly considers the application preferences of the user the agent represents. Think, for instance, of bilateral negotiation in e-commerce, where a buyer agent settles the product price according to user preferences such as product colour, payment method and delivery time (Fatima, Wooldridge, and Jennings 2006). In practice, users would express their preferences by ranking only a few representative examples instead of specifying a utility function (Tsipoukis et al. 2018). Hence, agents are uncertain about the complete user preferences and lack knowledge about the preferences and characteristics of their opponents (Baarslag et al. 2016). In such uncertain settings, predefined one-size-fits-all heuristics are unsuitable for representing a strategy, which must learn from opponent actions in different domains.

To this aim, we introduce ANESIA (Adaptive NEgotiation model for a Self-Interested Autonomous agent), an agent model that provides a learnable, adaptive and interpretable strategy under user and opponent preferences’ uncertainty. ANESIA builds on so-called strategy templates, i.e., parametric strategies that incorporate multiple negotiation tactics for the agent to choose from. A strategy template is described by a set of condition-action rules to be applied at different stages during the negotiation. Templates require no assumptions from the agent developer as to which tactic to choose during negotiation: from a template, we automatically learn the best combination of tactics to use at any time during the negotiation. Being logical combinations of individual tactics, the resulting strategies are interpretable and, thus, can be explained to the user. Although the template parameters are learned before a negotiation begins, ANESIA allows for online learning and adaptation as well.

ANESIA is an actor-critic architecture combining Deep Reinforcement Learning (DRL) (Lillicrap et al. 2016) with meta-heuristic optimisation. DRL allows ANESIA to learn a near-optimal threshold utility dynamically, adapting the strategy in different domains and against unknown opponents. ANESIA neither accepts nor proposes any bid below this utility. To deal with user preference uncertainty, we use a single-objective meta-heuristic (Yang and Karamanoglu 2020; Yang 2009) that handles large search spaces optimally, and converges towards a good solution in a limited number of iterations, using a limited population size (Talbi 2009). This estimated user model ensures that our agent receives a satisfactory utility from opponent bids. Also, ANESIA generates near-Pareto-optimal bids leading to win-win situations by combining multi-objective optimization (MOO) (Deb et al. 2002) and multi-criteria decision-making (Hwang and Yoon 1981) on top of estimated user and opponent models.

To evaluate the effectiveness of our approach against the state-of-the-art, we conduct simulation experiments based on the ANAC tournaments (Jonker et al. 2017). We have chosen domains available in the GENIUS tool (Lin et al. 2014), with different domain sizes and competitiveness levels (Williams et al. 2014). We play against winning agents with learning capabilities (from ANAC’17 and ’18) and agents that deal with user preference uncertainty (from ANAC’19). These agents span a wide range of strategies and techniques\textsuperscript{1}. Empirically, ANESIA outperforms existing strategies in terms of individual and social welfare utilities.

Related work
Existing approaches for a bilateral multi-

\textsuperscript{1}E.g., Genetic algorithm-SAGA, Bayesian approach-FSEGA, Gaussian process-AgentGP, Tabu Search-KakeSoba, Logistic Regression-AgentHerb, and Statistical frequency model-AgentGG.
issue strategy with reinforcement learning have focused on Tabular Q-learning to learn what to bid (Bakker et al. 2019) or DQN to learn when to accept a bid (Razeghi, Yavaz, and Aydoğan 2020). Unlike our work, these approaches are neither optimal for continuous action spaces nor can handle user preference uncertainty. The negotiation model of (Bagga et al. 2020) uses DRL to learn a complete strategy, but it is for single issue only. All the above approaches use DRL to learn acceptance or bidding strategies. Instead we learn a threshold utility as part of (possibly more sophisticated) tactics for acceptance and bidding.

Past work uses meta-heuristics to explore the outcome space and find desired bids or for bid generation (Silva et al. 2018; De Jonge and Sierra 2016; El-Ashmawi et al. 2020; Sato and Ito 2016; Kadono 2016; Klein et al. 2003; Sato and Ito 2016). We, too, use population-based meta-heuristic, but for estimating the user model that best agrees with the partial user preferences. In particular, we employ the Firefly Algorithm (FA) (Yang 2009) that has shown its effectiveness in continuous optimization, but has not been tested until now in the context of automated negotiation. Moreover, while the Genetic Algorithm NSGA-II (Deb et al. 2002) for MOO has been used previously to find multiple Pareto-optimal solutions during negotiation (Hashmi et al. 2013), we are the first to combine NSGA-II with TOPSIS (Hwang and Yoon 1981) to choose one best among a set of ranked near Pareto-optimal outcomes.

**Negotiation Environment**

We assume **bilateral negotiations** where two agents interact with each other in a domain \( D \), over \( n \) different independent issues, \( D = (I_1, I_2, \ldots, I_n) \), with each issue taking a finite set of \( k \) possible discrete or continuous values \( I_i = (v_1^i, \ldots, v_k^i) \). In our experiments, we consider issues with discrete values. An agent’s bid \( \omega \) is a mapping from each issue to a chosen value (denoted by \( c_i \) for the \( i \)-th issue), i.e., \( \omega = (v_1^1, \ldots, v_n^n) \). The set of all possible bids or outcomes is called outcome space \( \Omega \) s.t. \( \omega \in \Omega \). The outcome space is common knowledge to the negotiating parties and stays fixed during a single negotiation session.

**Negotiation protocol** Before the agents can begin the negotiation and exchange bids, they must agree on a negotiation protocol \( P \), which determines the valid moves agents can take at any state of the negotiation (Fatima, Wooldridge, and Jennings 2005). Here, we consider the **alternating offers protocol** (Rubinstein 1982) due to its simplicity and wide use. The set of protocol’s possible Actions are: \{offer(\( \omega \)), accept, reject\}. One of the agents (say \( A_u \)) starts a negotiation by making an offer \( X \) to the other agent (say \( A_o \)). Agent \( A_u \) can either accept or reject the offer. If it accepts, the negotiation ends with an agreement, otherwise \( A_o \) makes a counter-offer to \( A_u \). This process of making offers continues until one of the agents either accepts an offer (i.e., success) or the deadline is reached (i.e., failure). Moreover, we assume that the negotiations are sensitive to **time**, i.e. time impacts the utilities of the negotiating parties. In other words, the value of an agreement decreases over time.

**Utility** Each agent has a preference profile, reflecting the issues important to the agent, which values per issue are preferred over other values, and on the whole provides a (partial) ranking over all possible deals (Marsa-Maestre et al. 2014). In contrast to \( \Omega \), the agent’s preference profile is private information and is given in terms of a utility function \( U \). \( U \) is defined as a weighted sum of evaluation functions, \( e_i(v_i^o) \) as shown in (1). Each issue is evaluated separately and contributes linearly to \( U \). Such a \( U \) is a very common utility model and is also called a **Linear Additive Utility space**. Here, \( w_i \) are the normalized weights indicating each issue’s importance to the user and \( e_i(v_i^o) \) is an evaluation function that maps the \( v_i^o \) value of the \( i \)-th issue to a utility.

\[
U(\omega) = w_1 e_1(v_1^o) + \ldots + w_n e_n(v_n^o) = \sum_{i=1}^{n} w_i \cdot e_i(v_i^o), \text{ where } \sum_{i=1}^{n} w_i = 1
\]

(1)

Note that \( U \) does not take dependencies between issues into account. Whenever the negotiation terminates without any agreement, each negotiating party gets its corresponding utility based on the private reservation\(^2\) value (\( u_{res} \)).

In case the negotiation terminates with an agreement, each agent receives the discounted utility of the agreed bid, i.e.,

\[
U^d(\omega) = U(\omega) d_t^2, \text{ Here, } d_t \text{ is a discount factor in the interval } [0, 1] \text{ and } t \in [0, 1] \text{ is current normalized time.}
\]

**User and opponent utility models** In our settings, the negotiation environment is one with incomplete information, because the user utility model \( U_u \) is unknown. Only partial preferences are given, i.e., a partial order \( \preceq \) over \( B \) bids w.r.t. \( U_u \) s.t. \( \omega_1 \preceq \omega_2 \rightarrow U_u(\omega_1) \leq U_u(\omega_2) \). Hence, during the negotiation, one of the objectives of our agent is to derive an estimate \( \hat{U}_u \) of the real utility function \( U_u \) from the given partial preferences\(^3\). This leads to a single-objective constrained optimization problem,

\[
\max \rho \sum_{i=1}^{n} \hat{w}_i \cdot \hat{e}_i(v_i^o), \ B_{\preceq}
\]

(2)

s. t. \( \sum_{i=1}^{n} \hat{w}_i = 1 \)

where \( B_{\preceq} \) is the incomplete sequence of known bid preferences (ordered by \( \preceq \)), and \( \rho \) is a measure of ranking similarity (e.g., Spearman correlation) between the estimated ranking of \( \hat{U}_u \) and the true, but partial, bid ranking \( B_{\preceq} \). We also assume that our agent is unaware of the utility structure of its opponent agent \( U_o \). Hence, to increase the agreement rate over multiple issues, another objective of our agent is to generate the (near) Pareto-optimal solutions during the negotiation which can be defined as a MOO problem as follows:

\[
\max_{\omega \in \Omega} \left( \hat{U}_u(\omega), \hat{U}_o(\omega) \right)
\]

(3)

\(^2\)The reservation value is the minimum acceptable utility for an agent. It may vary for different parties and different domains. In our settings, it is the same for both parties.

\(^3\)Humans do not necessarily use an explicit utility function. Also, preference elicitation can be tedious for users since they have to interact with the system repeatedly (Baarslag and Kaisers 2017). As a result, agents should accurately represent users under minimal preference information (Tsimpoukis et al. 2018).
In (3), we have two objectives: $\tilde{U}_a$, the user’s estimated utility, and $\tilde{U}_o$, the opponent’s estimated utility. A bid $\omega^* \in \Omega$ is Pareto optimal if no other bid exists $\omega \in \Omega$ that Pareto-dominates $\omega^*$. In our case, a bid $\omega_1$ Pareto-dominates $\omega_2$ if:

$$
\begin{align*}
\left( \tilde{U}_a(\omega_1) &\geq \tilde{U}_a(\omega_2) \land \tilde{U}_o(\omega_1) \geq \tilde{U}_o(\omega_2) \right) \land \\
\left( \tilde{U}_a(\omega_1) &> \tilde{U}_a(\omega_2) \lor \tilde{U}_o(\omega_1) > \tilde{U}_o(\omega_2) \right)
\end{align*}
$$

(4)

**The ANESIA Model**

Our agent $A_o$ is situated in an environment $E$ (containing the opponent agent $A_o$) where at any time $t$, $A_o$ senses the current state $S_t$ of $E$ and represents it as a set of internal attributes. These include information derived from the sequence of previous bids offered by $A_o$ (e.g., utility of the best opponent bid so far $O_{best}$, average utility of all the opponent bids $O_{avg}$ and their variability $O_{sd}$) and information stored in the agent’s knowledge base (e.g., number of bids $B$ in the given partial order, $d_f$, $t_{res}$, $\Omega$, and $n$), and the current negotiation time $t$. This internal state representation, denoted with $s_t$, is used by the agent (in acceptance and bidding strategies) to decide what action $a_t$ to execute. Action execution then changes the state of the environment to $S_{t+1}$.

Learning in ANESIA$^4$ mainly consists of three components: Decide, Negotiation Experience, and Evaluate. **Decide** refers to the negotiation strategy for choosing a near-optimal action $a_t$ among a set of Actions at a particular state $s_t$ based on a protocol $P$. Action $a_t$ is derived via two functions, $f_a$ and $f_b$, for the acceptance and bidding strategies, respectively. Function $f_a$ takes as inputs $s_t$, a dynamic threshold utility $\bar{u}_t$ (defined later in the Methods section), the sequence of past opponent bids $\Omega^+_o$, and outputs a discrete action $a_t$ among accept or reject. When $f_a$ returns reject, $f_b$ computes what to bid next, with input $s_t$ and $\bar{u}_t$, see (5–6). This separation of acceptance and bidding strategies is not rare, see for instance (Baarslag et al. 2014).

$$
\begin{align*}
&f_a(s_t, \bar{u}_t, \Omega^+_o) = a_t, a_t \in \{\text{accept, reject}\} \\
&f_b(s_t, \bar{u}_t, \Omega^+_o) = a_t, a_t \in \{\text{offer}(\omega), \omega \in \Omega\}
\end{align*}
$$

(5) (6)

Since we assume incomplete user and opponent preference information, **Decide** uses the estimated models $\hat{U}_a$ and $\hat{U}_o$. In particular, $\hat{U}_o$ is estimated once before the negotiation starts by solving (2) and using the partial preference profile $\preceq$. This encourages agent autonomy and avoids continuous user preference elicitation. Similarly, $\hat{U}_o$ is estimated at time $t$ using information from $\Omega^+_o$, see Methods section for more details.

**Negotiation Experience** stores historical information about $N$ previous interactions of an agent with other agents. Experience elements are of the form $(s_t, a_t, r_t, s_{t+1})$, where $s_t$ is the internal state representation of the negotiation environment $E$, $a_t$ is the performed action, $r_t$ is a scalar reward received from the environment and $s_{t+1}$ is the new agent state after executing $a_t$.

Evaluate refers to a critic helping ANESIA learn the dynamic threshold utility $\bar{u}_t$, which evolves as new experience is collected. More specifically, it is a function of random $K$ ($K < N$) experiences fetched from the agent’s memory. Learning $\tilde{u}_t$ is **retrospective** since it depends on the reward $r_t$, obtained from $E$ by performing $a_t$ at $s_t$. The reward value depends on the (estimated) discounted utility of the last bid received from the opponent, $\omega^+_o$, or of the bid accepted by either parties $\omega^{acc}$ and defined as follows:

$$
\begin{align*}
&\bar{U}_a(\omega^{acc}, t), \quad \text{on agreement} \\
&\bar{U}_a(\omega^+_o, t), \quad \text{on received offer} \\
&-1, \quad \text{otherwise}
\end{align*}
$$

(7)

$\hat{U}_a(\omega, t)$ is the discounted reward of $\omega$ defined as:

$$
\hat{U}_a(\omega, t) = \bar{U}_a(\omega) \cdot d^t, d \in [0, 1]
$$

(8)

where $d$ is a temporal discount factor to encourage the agent to negotiate without delay. We should not confuse $d$, which is typically unknown to the agent, with the discount factor used to compute the utility of an agreed bid ($d_D$).

**Strategy templates:** One common way to define the acceptance ($f_a$) and bidding ($f_b$) strategies is via a combination of hand-crafted tactics that, by empirical evidence or domain knowledge, are known to work effectively. However, a fixed set of tactics might not well adapt to multiple different negotiation domains. ANESIA does not assume pre-defined strategies for $f_a$ and $f_b$ and learns these strategies offline. We run multiple negotiations between our agent and a pool of opponents. We select the combination of tactics that maximizes the true user utility over these negotiations. So, in this stage only, we assume that the true user model is known.

To enable strategy learning, we introduce **strategy templates**, i.e., parametric strategies incorporating a series of tactics, where each tactic is executed for a specific negotiation phase. The parameters describing the start and duration of each phase, as well as the particular tactic choice for that phase are all learnable (blue-colored in (9), (10)). Moreover, tactics can expose, in turn, learnable parameters themselves.

We assume a collection of acceptance and bidding tactics, $T_a$ and $T_b$. Each tactic $t_i \in T_a$ maps the agent state, threshold utility, opponent bid history, and (possibly empty) vector of learnable parameters $p$ into a utility value: if the agent is using tactic $t_{a,i}$ and $t_{a,i}(s_t, \bar{u}_t, \Omega^+_o, p) = u$, then it will not accept any offer with utility below $u$, see (9) below. Each tactic $t_b \in T_b$ is of the form $t_{b,i}(s_t, \bar{u}_t, \Omega^+_o, p) = \omega$ where $\omega \in \Omega$ is the bid returned by the tactic. An acceptance strategy template is a parametric function given by

$$
\Lambda^{n_{a,i}}_{t=1} t \in [t_i, t_{i+1}] \rightarrow \left( A^{n_{a,i}}_{t=1} a_{i,j} \to \hat{U}(\omega^+_o) \geq \omega_{i,j}(s_t, \bar{u}_t, \Omega^+_o, p_{i,j}) \right)
$$

(9)

where $n_a$ is the number of phases; $t_1 = 0, t_{n_{a}+1} = 1$, and $t_i = t_{i-1} + \delta_i$, where the $\delta_i$ parameter determines the duration of the $i$-th phase; for each phase $i$, the strategy template includes $n_{a,i}$ tactics to choose from: $c_{i,j}$ is a Boolean choice parameter determining whether tactic $t_{a,i,j} \in T_a$ should be used during the $i$-th phase. We note that (9) is a predicate.

$^4$See Appendix for the interaction between components of ANESIA architecture.
returning whether or not the opponent bid $\omega_t$ is accepted. Similarly, a bidding strategy template is defined by

$$
\bigcup_{i=1}^{n_b} \left\{ \begin{array}{ll}
t_{i,1} s_t, \bar{u}_t, \Omega_t, p_{i,1} & \text{if } t \in [t_i, t_{i+1}) \text{ and } c_{i,1} \\
\vdots \\
t_{i,n_i} s_t, \bar{u}_t, \Omega_t, p_{i,n_i} & \text{if } t \in [t_i, t_{i+1}) \text{ and } c_{i,n_i}
\end{array} \right.
$$

where $n_b$ is the number of phases, $n_i$ is the number of options for the $i$-th phase, and $t_{i,j} \in T_b$, $t_i$ and $c_{i,j}$ are defined as in the acceptance template. The particular libraries of tactics used in this work are discussed in the next Section. We stress that both (9) and (10) describe time-dependent strategies where a given choice of tactics is applied at different phases (denoted by the condition $t \in [t_i, t_{i+1})$).

**Methods**

**User modelling:** Before the negotiation begins, we estimate the user model $\hat{U}_u$ by finding the weights $\omega_i$ and utility values $c_{i,t}(\omega_i)$ for each issue $i$, see (1), so that the resulting bid ordering best fits the given partial order $\preceq$ of bids. To solve this optimization problem (2), we use FA (Yang 2009), a meta-heuristic inspired by the swarming and flashing behaviour of fireflies, because, in our preliminary analyses, it outperformed other traditional nature-inspired meta-heuristics such as GA and PSO (Rawat 2021). We compute the fitness of a candidate solution (i.e., the user model $\hat{U}_u$) as the Spearman’s rank correlation coefficient $\rho$ between the estimated ranking of $\hat{U}_u$ and the true, but partial, bid ranking $\preceq$. The coefficient $\rho \in [-1,1]$ is indeed a similarity measure between two rankings, assigning a value of 1 for identical and −1 for opposed rankings.

**Opponent modelling:** To derive an estimate of the opponent model $\hat{U}_o$ during negotiation, we use the distribution-based frequency model proposed in (Tunali, Aydo˘gan, and Sanchez-Anguix 2017). In this model, the empirical frequency of the issue values in $\Omega_t$ provides an educated guess on the opponent’s most preferred issue values. The issue weights are estimated by analysing the disjoint windows of $\Omega_t$, giving an idea of the shift of opponent’s preferences from its previous negotiation strategy over time.

**Utility threshold learning:** We use an actor-critic architecture with model-free deep reinforcement learning (i.e., Deep Deterministic Policy Gradient (DDPG) (Lillicrap et al. 2016)) to predict the target threshold utility $\bar{u}_t$. We consider a model-free RL approach because our problem is how to make an agent decide what target threshold utility to set next in a negotiation dialogue rather than predicting the new state of the environment, which implies model-based RL. Thus, $\bar{u}_t$ is expressed as a deep neural network function, which takes the agent state $s_t$ as an input (see previous section for the list of attributes). Prior to RL, our agent’s strategy is pre-trained with supervision from synthetic negotiation data. To collect supervision data, we use the GENIUS simulation environment (Lin et al. 2014), which supports multi-issue bilateral negotiation for different domains and user profiles. In particular, data was generated by running the winner of the ANAC’19 (AgentGG) against other strategies in three different domains and assuming no user preference uncertainties (Aydögan et al. 2020). This initial supervised learning (SL) stage helps our agent decrease the exploration time required for DRL during the negotiation, an idea primarily influenced by the work of (Bagga et al. 2020).

**Strategy learning:** The parameters of the acceptance and bidding strategy templates (9–10) are learned by running the FA meta-heuristic. We define the fitness of a particular choice of template parameters as the average true user utility over multiple negotiations rounds under the concrete strategy implied by those parameters. Negotiation data is obtained by running our agent on the GENIUS platform against three (readily available) opponents (AgentGG, Kakesoba and SAGA) in three different negotiation domains.

We now describe the libraries of tactics used in our templates. As for the acceptance tactics, we consider:

- $\hat{U}_u(\omega_t)$, the estimated utility of the bid that our agent would propose at time $t (\omega_t = f_b(s_t, \bar{u}_t, \Omega_t))$.
- $Q_{\hat{U}_o}(\Omega_t)(a \cdot t + b)$, where $\hat{U}_o(\Omega_t)$ is the distribution of (estimated) utility values of the bids in $\Omega_t$, $Q_{\hat{U}_o}(\Omega_t)(p)$ is the quantile function of such distribution, and $a$ and $b$ are learnable parameters. In other words, we consider the $p$-th best utility received from the agent, where $p$ is a learnable (linear) function of the negotiation time $t$. In this way, this tactic automatically and dynamically decides how much the agent should concede at time $t$.
- $\bar{u}_t$, the dynamic DRL-based utility threshold.
- $\bar{a}_t$, a fixed, but learnable, utility threshold.

The bidding tactics in our library are:

- $b_{\text{Boulware}}$, a bid generated by a time-dependent Boulware strategy (Fatima, Wooldridge, and Jennings 2001).
- $PS(a \cdot t + b)$ extracts a bid from the set of Pareto-optimal bids $PS$ (see (4)), derived using the NSGA-II algorithm (Deb et al. 2002) under $\hat{U}_u$ and $\hat{U}_o$. In particular, it selects the bid that assigns a weight of $a \cdot t + b$ to our agent utility (and $1 - (a \cdot t + b)$ to the opponent’s), where $a$ and $b$ are learnable parameters telling how this weight scales with the negotiation time $t$. The TOPSIS algorithm (Hwang and Yoon 1981) is used to derive such a bid, given the weights $a \cdot t + b$ as input.
- $b_{\text{opp}}(\omega_t)$, a tactic to generate a bid by manipulating the last bid received from the opponent $\omega_t$. This is modified in a greedy fashion by randomly changing the value of the least relevant issue (w.r.t. $\hat{U}$) of $\omega_t$.
- $\omega \sim U(\Omega_{\geq u_t})$, a random bid above our DRL-based utility threshold $u_t$.

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5Gravity, HandDealer, Kagent, Kakesoba, SAGA, and SACRA.

6Laptop, Holiday and Party.

7Meta-heuristics (instead of brute-force) for Pareto-optimal solutions have the potential to deal efficiently with continuous issues.

8$U(S)$ is the uniform distribution over $S$, and $\Omega_{\geq u_t}$ is the subset of $\Omega$ whose bids have estimated utility above $u_t$ w.r.t. $\hat{U}$. 
Below, we give an example of a concrete acceptance strategy learned in our experiments: it employs time-dependent quantile tactic during the middle of the negotiation, and the DRL threshold utility during the initial and final stages.

\[
\begin{align*}
    t \in [0.0, 0.4) & \rightarrow \bar{U}(\omega^*_t) \geq \bar{u}_i \land \bar{u} \\
    t \in [0.4, 0.7) & \rightarrow \bar{U}(\omega^*_t) \geq \bar{U}(\omega_t) \land Q_{\bar{U}}(\omega^*_t)(-0.67 \cdot t + 1.27) \\
    t \in [0.7, 0.95) & \rightarrow \bar{U}(\omega^*_t) \geq \bar{U}(\omega_t) \land Q_{\bar{U}}(\omega^*_t)(-0.21 \cdot t + 0.9) \\
    t \in [0.95, 1.0) & \rightarrow \bar{U}(\omega^*_t) \geq \bar{u}_t
\end{align*}
\]

Below is an example of a learned concrete bidding strategy: it behaves in a Boulware-like manner in the initial stage, after which it proposes near Pareto-optimal bids (between time 0.4 and 0.9) and opponent-oriented bid in the final stage.

\[
\begin{align*}
    t \in [0.0, 0.4) & \rightarrow \omega = b_{\text{Boulware}} \\
    t \in [0.4, 0.9) & \rightarrow \omega = PS(-0.75 \cdot t + 0.6) \\
    t \in [0.9, 1.0) & \rightarrow \omega = b_{\text{opp}}(\omega^*_t)
\end{align*}
\]

We stress that our approach allows to automatically devise such combinations of tactics so as to achieve optimal user utility, which would be infeasible manually.

### Performance metrics:

We measure the performance of each agent in terms of six widely-adopted metrics inspired by the ANAC competition:

- \(U_{\text{total}}\): The utility gained by an agent averaged over all the negotiations (↑);
- \(U_{\text{ind}}\): The utility gained by an agent averaged over all the successful negotiations (↑);
- \(U_{\text{nce}}\): The utility gained by both negotiating agents averaged over all successful negotiations (↑);
- \(P_{\text{avg}}\): Average minimal distance of agreements from the Pareto Frontier (↓);
- \(R_{\text{avg}}\): Average number of rounds before reaching the agreement (↓);
- \(S\%\): Proportion of successful negotiations (↑).

The first and second measures represent individual efficiency of an outcome, whereas the third and fourth correspond to the social efficiency of agreements.

### Experimental settings:

ANESIA is evaluated against state-of-the-art strategies that participated in ANAC’17, ’18, and ’19, and designed by different research groups independently. Each agent has no information about another agent’s strategies beforehand. Details of all these strategies are available in (Aydogan et al. 2018; Jonker and Ito 2020; Aydoğan et al. 2020). We assume incomplete information about user preferences, given in the form of \(B\) randomly-chosen partially-ordered bids. We evaluate ANESIA on 8 negotiation domains which are different from each other in terms of size and opposition (Baarslag et al. 2013) to ensure good negotiation characteristics and to reduce any biases. The domain size refers to the number of issues, whereas opposition refers to the minimum distance from all possible outcomes to the point representing complete satisfaction of both negotiation parties (1,1). For our experiments, we choose readily-available 3 small-sized, 2 medium-sized, and 3 large-sized domains. Out of these domains, 2 are with high, 3 with medium and 3 with low opposition (see (Williams et al. 2014) for more details).

For each configuration, each agent plays both roles in the negotiation to compensate for any utility differences in the preference profiles. We call user profile the agent’s role along with the user’s preferences. We set two user preferences uncertainties for each role: \(|B| = 5\%|\Omega|\) and \(|B| = 10\%|\Omega|\). Also, we set the \(u_{\text{res}}\) and \(d_D\) to their respective default values, whereas the deadline is set to 60s, normalized in \([0, 1]\) (known to both negotiating parties in advance).

Regarding the optimization algorithms, for FA (hypotheses A and C), we choose a population size of 20 and 200 generations for user model estimation and learning of strategy template parameters. We also set the maximum attractiveness value to 1.0 and absorption coefficient to 0.01. For NSGA-II (hypothesis B), we choose the population size of \(2\% \times |\Omega|\), 2 generations and mutation count of 0.1.

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\(^9\)The value of opposition reflects the competitiveness between parties in the domain. Strong opposition means a gain of one party is at the loss of the other, whereas, weak opposition means that both parties either lose or gain simultaneously (Baarslag et al. 2013).
these hyperparameters, on our machine the run-time of NSGA-II never exceeded the given timeout of 10s for deciding an action at each turn, while being able to retrieve empirically good solutions.

**Empirical Evaluation**

**Hypothesis A: User Modelling** We used two measures to determine the difference between \( \hat{U}_u \) and \( U_{\text{true}} \) (Wachowicz, Kersten, and Roszkowska 2019): First, **Ordinal accuracy** (OA) measures the proportion of bids put by \( \hat{U} \) in the correct rank order (i.e., as defined by the true user model), where an OA value of 1 implies a 100% correct ranking. Second, to capture the scale of cardinal errors, **Cardinal Inaccuracy** (CI) measures the differences in ratings assigned in the estimated and true user models for all the elements in domain \( D \).

We produced results in 8 domains and two profiles (5% and 10% of total possible bids) which are averaged over 10 simulations as shown in Table 1. All the values of OA (↑) and CI (↓), in each domain, for both the user profiles, are ≥ 0.67 and ≤ 0.90 respectively, which is quite accurate given the uncertainty and the fact that the CI value \( \propto |D| \).

**Hypothesis B: Pareto-Optimal Bids** We used a popular metric called Inverted Generational Distance (IGD) (Cheng, Shi, and Qin 2012) to compare the Pareto Fronts found by the ANSA-II and the ground truth (found via brute force). Small IGD values suggest good convergence of solutions to the Pareto Front and their good distribution over the entire Pareto Front. Table 2 demonstrates the potential of NSGA-II for generating the Pareto-optimal bids as well as the closeness of true utility models.

**Hypothesis C: ANESIA outperforms “teacher” strategies**

We performed a total of 1440 negotiation sessions to evaluate the performance of ANESIA against the three “teacher” strategies (AgentGG, KakeSoba and SAGA) in three domains (Laptop, Holiday, and Party) for two different profiles (\( |B| = 10, 20 \)). These strategies were used to collect the dataset in the same domains for supervised training before the DRL process begins. Table 3 demonstrates the average results over all the domains and profiles for each agent. Clearly, **ANESIA outperforms the “teacher” strategies in terms of \( \bar{U}_{\text{soc}} \) (i.e., individual efficiency), \( U_{\text{soc}} \), and \( P_{\text{avg}} \) (i.e., social efficiency).**

**Hypothesis D: Adaptive Behaviour of ANESIA agent**

Further evaluated the performance of ANESIA on agents (from ANAC’17, ANAC’18 and ANAC’19) unseen during training. For this, we performed a total of 23040 negotiation sessions. Results in Table 4(A) are averaged over all domains and profiles, and demonstrate that ANESIA learns to make the optimal choice of tactics to be used at run time and outperforms the other 8 strategies in terms of \( \bar{U}_{\text{soc}} \).
and ANAC’18 agents since, like our approach, they enable learning from past negotiations.

To this end, we note that ANESIA uses prior negotiation data from AgentGG to pre-train the DRL-based utility threshold and adjust the selection of tactics from the templates. The effectiveness of our approach is demonstrated by the fact that ANESIA outperforms the same agents it was trained on (see Hypothesis C), but, crucially, does so also on domains and opponents unseen during training. We further stress that the obtained performance metrics are affected only in part by an adequate pre-training of the strategies: the quality of the estimated user and opponent models – derived without any prior training data from other agents – plays an important role too. The results in Tables 4 (A to C) evidence that our agent consistently outperforms its opponents in terms of individual and social efficiency, demonstrating that ANESIA can learn to adapt at run-time to different negotiation settings and against different unknown opponents.

**Conclusions**

ANESIA is a novel agent model encapsulating different types of learning to support negotiation over multiple issues and under user preference uncertainty. An ANESIA agent uses stochastic search based on FA for user modelling and combines NSGA-II and TOPSIS for generating Pareto bids during negotiation. It further exploits strategy templates to learn the best combination of acceptances and bidding tactics at any negotiation time, and among its tactics, it uses an adaptive target threshold utility learned using the DDPG algorithm. We have empirically evaluated the performance of ANESIA against the winning agent strategies of ANAC’17, ’18 and ’19 competitions in different settings, showing that our agent both outperforms opponents known at training time and can effectively transfer its knowledge to environments with previously unseen opponent agents and domains.

An open problem worth pursuing in the future is how to update the synthesized template strategy dynamically.

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Table 4: Performance comparison of ANESIA against other ANAC winning strategies averaged over all the 8 domains and two uncertain preference profiles in each domain. See Appendix for the separate results for each domain. ANAC’19 agents (●) have uncertain user preferences, and no learning capabilities. ANAC’17 (*) and ANAC’18 (○) agents can learn from experience and are given real user preferences. In blue are the best among ANESIA and ANAC’19 agents. In purple, the overall best.

![Figure 1: Increase in Dynamic Threshold Utility using DRL](image-url)

Figure 1: Increase in Dynamic Threshold Utility using DRL and ANAC’18 agents since, like our approach, they enable learning from past negotiations.
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Figure 2: Interaction between the components of ANESIA

| Metric          | ANESIA | AgentGG | KakeSoba | SAGA |
|-----------------|--------|---------|---------|------|
| $|B| = 5$              |        |         |         |      |
| $R_{avg}$       | 476.81 | 259.35  | 1224.04 | 1066.18 |
| $R_{avg}$       | 847.48 | 453.35  | 841.16  | 1710.8 |
| $P_{avg}$       | 0.15 ± 0.57 | 0.17 ± 0.26 | 0.35 ± 0.44 | 0.17 ± 0.34 |
| $U_{soc}$       | 1.79 ± 0.81 | 1.72 ± 0.78 | 1.33 ± 0.52 | 1.41 ± 0.49 |
| $U_{ind}$       | 0.46 ± 0.42 | 0.51 ± 0.39 | 0.73 ± 0.34 | 0.8 ± 0.26 |
| $U_{soc}$       | 0.88 ± 0.11 | 0.88 ± 0.01 | 0.87 ± 0.13 | 0.73 ± 0.11 |
| $P_{soc}$       | 0.56   | 0.64    | 0.83    | 0.92  |
| $|B| = 10$             |        |         |         |      |
| $R_{avg}$       | 256.27 | 254.62  | 258.61  | 254.73  |
| $R_{soc}$       | 393.1  | ±446.96 | 4523.85 | 4559.91 |
| $P_{soc}$       | 0.02 ± 0.26 | 0.05 ± 0.26 | 0.07 ± 0.18 | 0.07 ± 0.18 |
| $U_{soc}$       | 1.57 ± 0.81 | 1.50 ± 0.8 | 1.26 ± 0.63 | 1.34 ± 0.62 |
| $P_{soc}$       | 0.47 ± 0.48 | 0.5 ± 0.48 | 0.72 ± 0.33 | 0.77 ± 0.32 |
| $|B| = 10$             |        |         |         |      |
| $R_{avg}$       | 213.2  | 229.98  | 508.04  | 673.01  |
| $R_{soc}$       | 239.1  | ±446.96 | 4523.85 | 4559.91 |
| $P_{soc}$       | 0.96 ± 0.08 | 0.95 ± 0.09 | 0.91 ± 0.11 | 0.89 ± 0.11 |
| $P_{soc}$       | 0.48   | 0.52    | 0.76    | 0.85  |
| $|B| = 10$             |        |         |         |      |
| $R_{avg}$       | 213.2  | 229.98  | 508.04  | 673.01  |
| $R_{soc}$       | 239.1  | ±446.96 | 4523.85 | 4559.91 |
| $P_{soc}$       | 0.96 ± 0.08 | 0.95 ± 0.09 | 0.91 ± 0.11 | 0.89 ± 0.11 |
| $P_{soc}$       | 0.48   | 0.52    | 0.76    | 0.85  |

Table 5: Performance Comparison of ANESIA with “teacher” strategies.
| Agent          | $R_{avg}(\bar{\mu})$ | $P_{avg}(\bar{\mu})$ | $U_{soc}(\bar{\mu})$ | $U_{total}^\text{bias}(\bar{\mu})$ | $U_{total}^\text{std}(\bar{\mu})$ | $S_{\mu}(\bar{\mu})$ |
|---------------|----------------------|------------------------|-----------------------|-------------------------------------|-------------------------------|----------------------|
| ANESIA        | 502.96 ± 350.71      | 0.06 ± 0.53            | 1.76 ± 0.79          | 0.69 ± 0.21                         | 0.92 ± 0.11                   | 0.48                 |
| AgentGP ⋅     | 774.69 ± 562.07      | 0.59 ± 0.53            | 0.72 ± 0.79          | 0.69 ± 0.21                         | 0.92 ± 0.06                   | 0.45                 |
| FSEGA2019 ⋅  | 1023.41 ± 1450.49    | 0.07 ± 0.26            | 1.49 ± 0.38          | 0.77 ± 0.14                         | 0.78 ± 0.13                   | 0.94                 |
| AgentHerb ⋉   | 10.58 ± 3.59         | 0.0 ± 0.01             | 1.55 ± 0.11          | 0.59 ± 0.14                         | 0.59 ± 0.14                   | 1.00                 |
| Agent33 ⋈     | 1556.13 ± 2104.58    | 0.19 ± 0.41            | 1.3 ± 0.6            | 0.72 ± 0.13                         | 0.76 ± 0.09                   | 0.82                 |
| Sontag ⋈      | 1285.67 ± 1931.73    | 0.08 ± 0.27            | 1.47 ± 0.41          | 0.73 ± 0.12                         | 0.75 ± 0.11                   | 0.93                 |
| AgreeableAgent ⋈ | 2206.13 ± 2724.1    | 0.18 ± 0.4             | 1.32 ± 0.59          | 0.82 ± 0.18                         | 0.88 ± 0.12                   | 0.84                 |
| PonpokoAgent ⋆ | 1988.18 ± 2717.28   | 0.19 ± 0.41            | 1.29 ± 0.6           | 0.82 ± 0.16                         | 0.88 ± 0.07                   | 0.82                 |
| ParsCat2 ⋆    | 1490.62 ± 1833.53    | 0.09 ± 0.3             | 1.44 ± 0.44          | 0.77 ± 0.14                         | 0.79 ± 0.12                   | 0.92                 |

Table 6: Performance of fully-fledged ANESIA in the domain AIRPORT (1440 × 2 profiles = 2880 simulations)

| Agent          | $R_{avg}(\bar{\mu})$ | $P_{avg}(\bar{\mu})$ | $U_{soc}(\bar{\mu})$ | $U_{total}^\text{bias}(\bar{\mu})$ | $U_{total}^\text{std}(\bar{\mu})$ | $S_{\mu}(\bar{\mu})$ |
|---------------|----------------------|------------------------|-----------------------|-------------------------------------|-------------------------------|----------------------|
| ANESIA        | 387.84 ± 297.52      | 0.06 ± 0.27            | 1.64 ± 0.04          | 0.62 ± 0.36                         | 0.96 ± 0.06                   | 0.52                 |
| AgentGP ⋅     | 646.55 ± 497.55      | 0.25 ± 0.27            | 0.69 ± 0.68          | 0.61 ± 0.34                         | 0.92 ± 0.06                   | 0.54                 |
| FSEGA2019 ⋅  | 814.29 ± 813.53      | 0.05 ± 0.15            | 1.13 ± 0.4           | 0.74 ± 0.19                         | 0.79 ± 0.13                   | 0.92                 |
| AgentHerb ⋉   | 3.13 ± 1.23          | 0.01 ± 0.02            | 1.54 ± 0.11          | 0.56 ± 0.12                         | 0.56 ± 0.12                   | 1.00                 |
| Agent33 ⋈     | 182.67 ± 151.37      | 0.0 ± 0.01             | 1.46 ± 0.12          | 0.63 ± 0.13                         | 0.63 ± 0.13                   | 1.00                 |
| Sontag ⋈      | 712.1 ± 746.85       | 0.06 ± 0.17            | 1.15 ± 0.45          | 0.72 ± 0.2                          | 0.78 ± 0.12                   | 0.89                 |
| AgreeableAgent ⋈ | 1192.59 ± 1179.95   | 0.08 ± 0.19            | 0.93 ± 0.47          | 0.79 ± 0.27                         | 0.88 ± 0.16                   | 0.86                 |
| PonpokoAgent ⋆ | 1091.71 ± 1197.91   | 0.12 ± 0.22            | 0.91 ± 0.54          | 0.75 ± 0.27                         | 0.89 ± 0.07                   | 0.78                 |
| ParsCat2 ⋆    | 925.64 ± 884.29      | 0.06 ± 0.17            | 1.04 ± 0.44          | 0.76 ± 0.22                         | 0.82 ± 0.13                   | 0.89                 |

Table 7: Performance of fully-fledged ANESIA in the domain Camera (1440 × 2 profiles = 2880 simulations)
| Agent          | $R_{avg}(\uparrow)$ | $P_{avg}(\uparrow)$ | $U_{soc}(\uparrow)$ | $U_{total}(\uparrow)$ | $U_{ind}(\uparrow)$ | $S_{avg}(\uparrow)$ |
|----------------|---------------------|----------------------|---------------------|----------------------|---------------------|---------------------|
| ANESIA         | 1885.12 ± 220.17    | 0.59 ± 0.24          | 1.15 ± 0.36         | 0.57 ± 0.17          | 0.57 ± 0.17         | 0.57 ± 0.04         |
| Agent33        | 776.26 ± 137.29     | 0.36 ± 0.34          | 0.58 ± 0.59         | 0.71 ± 0.21          | 0.92 ± 0.02         | 0.49 ± 0.01         |
| FSEGA2019      | 227.55 ± 94.34      | 0.53 ± 0.29          | 0.26 ± 0.46         | 0.6 ± 0.18           | 0.91 ± 0.06         | 0.24 ± 0.00         |
| AgentHerb      | 209.5 ± 390.96      | 0.01 ± 0.03          | 1.11 ± 0.13         | 0.21 ± 0.15          | 0.21 ± 0.15         | 1.00 ± 0.00         |
| AgreeableAgent | 16164.98 ± 19874.32 | 0.01 ± 0.03          | 1.11 ± 0.13         | 0.21 ± 0.15          | 0.21 ± 0.15         | 1.00 ± 0.00         |
| Agent33        | 9736.06 ± 11596.61  | 0.11 ± 0.24          | 0.98 ± 0.42         | 0.5 ± 0.16           | 0.5 ± 0.17          | 0.86 ± 0.06         |
| Sontag         | 20110.81 ± 19539.26 | 0.21 ± 0.31          | 0.69 ± 0.45         | 0.69 ± 0.19          | 0.77 ± 0.18         | 0.71 ± 0.18         |
| AgreeableAgent | 35654.55 ± 36140.39 | 0.15 ± 0.29          | 1.04 ± 0.41         | 0.57 ± 0.30          | 0.62 ± 0.29         | 0.88 ± 0.08         |
| PompokoAgent   | 18600.12 ± 19064.62 | 0.33 ± 0.34          | 0.54 ± 0.52         | 0.69 ± 0.20          | 0.87 ± 0.11         | 0.52 ± 0.00         |
| ParsCat2       | 13441.85 ± 13936.75 | 0.25 ± 0.32          | 0.72 ± 0.52         | 0.24 ± 0.18          | 0.71 ± 0.18         | 0.65 ± 0.06         |

Table 8: Performance of fully-fledged ANESIA in the domain Energy (1440 × 2 profiles = 2880 simulations)

| Agent          | $R_{avg}(\downarrow)$ | $P_{avg}(\downarrow)$ | $U_{soc}(\downarrow)$ | $U_{total}(\downarrow)$ | $U_{ind}(\downarrow)$ | $S_{avg}(\downarrow)$ |
|----------------|-----------------------|------------------------|-----------------------|-------------------------|-----------------------|-----------------------|
| ANESIA         | 2207.35 ± 1240.7      | 0.74 ± 0.36            | 1.21 ± 0.44           | 0.39 ± 0.28             | 0.96 ± 0.05           | 0.19 ± 0.00           |
| Agent33        | 157.6 ± 278.3         | 0.07 ± 0.21            | 1.13 ± 0.28           | 0.60 ± 0.31             | 0.62 ± 0.3            | 0.94 ± 0.00           |
| FSEGA2019      | 235.12 ± 104.56       | 0.48 ± 0.45            | 0.59 ± 0.6            | 0.56 ± 0.32             | 0.89 ± 0.06           | 0.49 ± 0.00           |
| AgentHerb      | 200.51 ± 378.53       | 0.01 ± 0.03            | 1.15 ± 0.08           | 0.21 ± 0.15             | 0.21 ± 0.15           | 1.00 ± 0.00           |
| Agent33        | 24080.45 ± 23684.48   | 0.14 ± 0.3             | 1.14 ± 0.44           | 0.53 ± 0.2              | 0.57 ± 0.18           | 0.87 ± 0.07           |
| Sontag         | 33677.34 ± 37660.47   | 0.4 ± 0.43             | 0.73 ± 0.62           | 0.54 ± 0.26             | 0.74 ± 0.14           | 0.59 ± 0.00           |
| AgreeableAgent | 35654.55 ± 36140.39   | 0.15 ± 0.29            | 1.04 ± 0.41           | 0.57 ± 0.30             | 0.62 ± 0.29           | 0.88 ± 0.08           |
| PompokoAgent   | 37176.59 ± 37296.11   | 0.47 ± 0.45            | 0.61 ± 0.61           | 0.57 ± 0.32             | 0.88 ± 0.08           | 0.50 ± 0.00           |
| ParsCat2       | 24819.35 ± 24326.69   | 0.35 ± 0.44            | 0.82 ± 0.64           | 0.52 ± 0.24             | 0.68 ± 0.16           | 0.63 ± 0.00           |

Table 9: Performance of fully-fledged ANESIA in the domain Grocery (1440 × 2 profiles = 2880 simulations)
Table 10: Performance of fully-fledged ANESIA in the domain Fitness (1440 × 2 profiles = 2880 simulations)

| Agent          | $R_{avg}(\%)$ | $P_{avg}(\%)$ | $U_{soc}(\%)$ | $U_{total}(\%)$ | $U_{indi}(\%)$ | $S_{ud}(\%)$ |
|----------------|---------------|----------------|---------------|------------------|----------------|--------------|
| ANESIA         | 10.33 ± 1.05  | 0.0 ± 0.0      | 1.57 ± 0.04   | 1.0 ± 0.0        | 1.0 ± 0.0      | 1.00         |
| AgentGP ⋄      | 7520.99 ± 8454.27 | 0.01 ± 0.0    | 1.52 ± 0.04   | 0.93 ± 0.03      | 0.93 ± 0.03    | 1.00         |
| FSEGA2019 ⋄   | 1047.27 ± 739.83 | 0.01 ± 0.0    | 1.56 ± 0.07   | 0.77 ± 0.12      | 0.77 ± 0.12    | 1.00         |
| AgentHerb ⋄   | 12.52 ± 3.01    | 0.01 ± 0.0    | 1.55 ± 0.07   | 0.84 ± 0.09      | 0.84 ± 0.09    | 1.00         |
| Agent33 ⋄     | 102.13 ± 10180.53 | 0.01 ± 0.0    | 1.57 ± 0.05   | 0.76 ± 0.12      | 0.76 ± 0.12    | 1.00         |
| Sontag ⋄      | 19677.92 ± 15053.14 | 0.01 ± 0.0    | 1.57 ± 0.04   | 0.9 ± 0.06       | 0.9 ± 0.06     | 1.00         |
| AgreeableAgent ⋄ | 16583.31 ± 12421.79 | 0.01 ± 0.0    | 1.57 ± 0.05   | 0.84 ± 0.1       | 0.84 ± 0.1     | 1.00         |

Table 11: Performance of fully-fledged ANESIA in the domain Flight Booking (1440 × 2 profiles = 2880 simulations)

| Agent          | $R_{avg}(\%)$ | $P_{avg}(\%)$ | $U_{soc}(\%)$ | $U_{total}(\%)$ | $U_{indi}(\%)$ | $S_{ud}(\%)$ |
|----------------|---------------|----------------|---------------|------------------|----------------|--------------|
| ANESIA         | 457.11 ± 307.19 | 0.04 ± 0.28    | 1.54 ± 0.63   | 0.66 ± 0.21      | 0.9 ± 0.16     | 0.43         |
| AgentGP ⋄      | 664.13 ± 477.03 | 0.35 ± 0.28    | 0.56 ± 0.68   | 0.66 ± 0.2       | 0.9 ± 0.08     | 0.41         |
| FSEGA2019 ⋄   | 1021.27 ± 1249.01 | 0.09 ± 0.2    | 1.14 ± 0.46   | 0.78 ± 0.15      | 0.82 ± 0.12    | 0.87         |
| AgentHerb ⋄   | 7.7 ± 3.9      | 0.01 ± 0.05    | 1.37 ± 0.09   | 0.42 ± 0.13      | 0.42 ± 0.13    | 1.00         |
| Agent33 ⋄     | 543.69 ± 758.12 | 0.05 ± 0.13    | 1.26 ± 0.34   | 0.52 ± 0.11      | 0.52 ± 0.11    | 0.95         |
| Sontag ⋄      | 1041.66 ± 1365.84 | 0.1 ± 0.21    | 1.13 ± 0.51   | 0.75 ± 0.15      | 0.82 ± 0.11    | 0.84         |
| AgreeableAgent ⋄ | 1838.85 ± 1648.32 | 0.12 ± 0.22   | 0.98 ± 0.47   | 0.79 ± 0.17      | 0.85 ± 0.12    | 0.82         |
| PonpokoAgent ⋄ | 1500.68 ± 1771.53 | 0.12 ± 0.22   | 1.05 ± 0.51   | 0.81 ± 0.16      | 0.88 ± 0.06    | 0.82         |
| ParsCat2 ⋄    | 1143.01 ± 1320.89 | 0.09 ± 0.2    | 1.12 ± 0.45   | 0.78 ± 0.17      | 0.82 ± 0.14    | 0.86         |

| Agent          | $R_{avg}(\%)$ | $P_{avg}(\%)$ | $U_{soc}(\%)$ | $U_{total}(\%)$ | $U_{indi}(\%)$ | $S_{ud}(\%)$ |
|----------------|---------------|----------------|---------------|------------------|----------------|--------------|
| ANESIA         | 479.79 ± 300.63 | 0.02 ± 0.4     | 1.64 ± 0.66   | 0.56 ± 0.34      | 0.89 ± 0.15    | 0.49         |
| AgentGP ⋄      | 698.1 ± 301.62 | 0.47 ± 0.39    | 0.61 ± 0.7    | 0.53 ± 0.33      | 0.43 ± 0.15    | 0.43         |
| FSEGA2019 ⋄   | 1099.44 ± 1361.39 | 0.12 ± 0.27   | 1.23 ± 0.48   | 0.75 ± 0.22      | 0.83 ± 0.12    | 0.87         |
| AgentHerb ⋄   | 9.17 ± 2.93    | 0.01 ± 0.03    | 1.38 ± 0.09   | 0.43 ± 0.15      | 0.43 ± 0.15    | 1.00         |
| Agent33 ⋄     | 741.04 ± 1130.56 | 0.04 ± 0.12    | 1.35 ± 0.24   | 0.51 ± 0.15      | 0.51 ± 0.14    | 0.98         |
| Sontag ⋄      | 1103.64 ± 1566.31 | 0.12 ± 0.28   | 1.24 ± 0.52   | 0.72 ± 0.22      | 0.8 ± 0.11     | 0.86         |
| AgreeableAgent ⋄ | 1981.51 ± 1924.17 | 0.11 ± 0.26   | 1.17 ± 0.44   | 0.75 ± 0.25      | 0.82 ± 0.19    | 0.88         |
| PonpokoAgent ⋄ | 1565.29 ± 1663.12 | 0.15 ± 0.3    | 1.16 ± 0.54   | 0.78 ± 0.24      | 0.88 ± 0.06    | 0.83         |
| ParsCat2 ⋄    | 1135.35 ± 1244.4 | 0.12 ± 0.28   | 1.21 ± 0.5    | 0.74 ± 0.24      | 0.83 ± 0.14    | 0.85         |
### Table 12: Performance of fully-fledged ANESIA in the domain Iter (1440 × 2 profiles = 2880 simulations)

| Agent          | $R_{avg}(\%)$ | $P_{avg}(\%)$ | $U_{soc}(\%)$ | $U_{total}(\%)$ | $U_{ref}(\%)$ | $S_{ref}(\%)$ |
|----------------|--------------|----------------|----------------|-----------------|---------------|-------------|
| ANESIA         | 591.32 ± 412.93 | 0.06 ± 0.24 | 1.17 ± 0.41 | 0.36 ± 0.27 | 0.99 ± 0.03 | 0.15         |
| AgentGP •      | 745.37 ± 490.4 | 0.46 ± 0.3   | 0.35 ± 0.53  | 0.43 ± 0.28 | 0.83 ± 0.16 | 0.32         |
| FSEGA2019 •    | 1796.16 ± 2832.98 | 0.2 ± 0.3   | 0.79 ± 0.52  | 0.59 ± 0.26 | 0.74 ± 0.16 | 0.70         |

### Table 13: Performance of fully-fledged ANESIA in the domain Outfit (1440 × 2 profiles = 2880 simulations)

| Agent          | $R_{avg}(\%)$ | $P_{avg}(\%)$ | $U_{soc}(\%)$ | $U_{total}(\%)$ | $U_{ref}(\%)$ | $S_{ref}(\%)$ |
|----------------|--------------|----------------|----------------|-----------------|---------------|-------------|
| ANESIA         | 516.7 ± 352.5 | 0.05 ± 0.4    | 1.57 ± 0.73   | 0.67 ± 0.37 | 0.99 ± 0.02 | 0.56         |
| AgentGP •      | 786.93 ± 580.41 | 0.39 ± 0.4   | 0.83 ± 0.79  | 0.61 ± 0.34 | 0.93 ± 0.07 | 0.53         |
| FSEGA2019 •    | 854.16 ± 890.84 | 0.05 ± 0.19  | 1.44 ± 0.39  | 0.79 ± 0.18 | 0.83 ± 0.11 | 0.94         |
| Agent                | $R_{avg}(\%)$ | $P_{avg}(\%)$ | $U_{avg}(\%)$ | $U_{total}(\%)$ | $U_{grid}(\%)$ | $S_{grid}(\%)$ |
|----------------------|----------------|---------------|----------------|-----------------|----------------|----------------|
| ANESIA-DRL           | 418.88 ± 381.14 | 0.51 ± 0.5 | 1.43 ± 0.32 | 0.61 ± 0.13 | 0.86 ± 0.17 | 0.36 ± 0.13 |
| AgentGP •            | 159.14 ± 137.0 | 0.27 ± 0.22 | 1.28 ± 0.23 | 0.5 ± 0.23 | 1.40 ± 0.00 | 0.63 ± 0.13 |
| FSEGA2019 •          | 994.88 ± 1324.84 | 0.1 ± 0.2 | 1.41 ± 0.34 | 0.75 ± 0.17 | 0.75 ± 0.16 | 0.95 ± 0.16 |
| AgentHerb o          | 9.9 ± 3.64      | 0.19 ± 0.22 | 2.35 ± 0.34 | 0.55 ± 0.16 | 0.55 ± 0.17 | 0.93 ± 0.00 |
| Agent33 o            | 971.03 ± 1467.42 | 0.25 ± 0.31 | 1.16 ± 0.44 | 0.54 ± 0.17 | 0.54 ± 0.17 | 0.94 ± 0.00 |
| Sontag o             | 1101.3 ± 1448.19 | 0.14 ± 0.28 | 1.35 ± 0.41 | 0.72 ± 0.19 | 0.72 ± 0.18 | 0.94 ± 0.00 |
| AgreeableAgent o     | 1778.16 ± 2007.86 | 0.17 ± 0.32 | 1.29 ± 0.45 | 0.79 ± 0.2 | 0.81 ± 0.19 | 0.92 ± 0.00 |
| PonpokoAgent *       | 1716.79 ± 2102.82 | 0.21 ± 0.35 | 1.24 ± 0.5 | 0.81 ± 0.15 | 0.86 ± 0.1 | 0.88 ± 0.00 |
| ParsCat2 *           | 1137.39 ± 1502.72 | 0.14 ± 0.27 | 1.35 ± 0.38 | 0.72 ± 0.19 | 0.73 ± 0.19 | 0.95 ± 0.00 |

Table 14: Performance of ANESIA-DRL - Ablation Study 1 - over domain Airport (1440 × 2 profiles = 2880 simulations)

| Agent                | $R_{avg}(\%)$ | $P_{avg}(\%)$ | $U_{avg}(\%)$ | $U_{total}(\%)$ | $U_{grid}(\%)$ | $S_{grid}(\%)$ |
|----------------------|----------------|---------------|----------------|-----------------|----------------|----------------|
| ANESIA-DRL           | 328.8 ± 325.31 | 0.07 ± 0.24 | 1.52 ± 0.61 | 0.53 ± 0.26 | 0.84 ± 0.14 | 0.58 ± 0.15 |
| AgentGP •            | 116.17 ± 102.35 | 0.07 ± 0.15 | 1.1 ± 0.43 | 0.7 ± 0.21 | 0.74 ± 0.17 | 0.92 ± 0.00 |
| FSEGA2019 •          | 832.59 ± 857.95 | 0.07 ± 0.12 | 1.05 ± 0.37 | 0.72 ± 0.02 | 0.75 ± 0.18 | 0.95 ± 0.00 |
| AgentHerb o          | 4.42 ± 3.69    | 0.03 ± 0.08 | 1.51 ± 0.15 | 0.59 ± 0.13 | 0.59 ± 0.13 | 1.00 ± 0.00 |
| Agent33 o            | 255.76 ± 452.66 | 0.07 ± 0.09 | 1.34 ± 0.17 | 0.62 ± 0.15 | 0.62 ± 0.15 | 1.00 ± 0.00 |
| Sontag o             | 754.03 ± 784.9 | 0.08 ± 0.15 | 1.06 ± 0.41 | 0.72 ± 0.18 | 0.76 ± 0.13 | 0.92 ± 0.00 |
| AgreeableAgent o     | 1142.5 ± 1144.36 | 0.07 ± 0.13 | 0.89 ± 0.4 | 0.79 ± 0.22 | 0.82 ± 0.17 | 0.93 ± 0.00 |
| PonpokoAgent *       | 1066.46 ± 999.52 | 0.12 ± 0.18 | 0.86 ± 0.44 | 0.75 ± 0.23 | 0.84 ± 0.1 | 0.85 ± 0.00 |
| ParsCat2 *           | 875.01 ± 985.44 | 0.08 ± 0.13 | 1.02 ± 0.38 | 0.73 ± 0.18 | 0.76 ± 0.14 | 0.94 ± 0.00 |

Table 15: Performance of ANESIA-DRL - Ablation Study 1 - over domain Camera (1440 × 2 profiles = 2880 simulations)
Table 16: Performance of ANESIA-DRL - Ablation Study1 - over domain Energy (1440 × 2 profiles = 2880 simulations)

| Agent            | $R_{avg}(\downarrow)$ | $P_{avg}(\downarrow)$ | $U_{soc}(\dagger)$ | $U_{total}(\dagger)$ | $U_{soc}(\dagger)$ | $S_R(\dagger)$ |
|------------------|------------------------|------------------------|---------------------|-----------------------|---------------------|-----------------|
| ANESIA-DRL       | 1332.93 ± 1083.96      | 0.09 ± 0.39            | 0.46 ± 0.55         | 1.1 ± 0.22            | 0.36 ± 0.16        | 0.41            |
| AgentGP ⚫        | 46.98 ± 167.92         | 0.55 ± 0.39            | 0.53 ± 0.57         | 0.4 ± 0.19             | 0.56 ± 0.16        | 0.47             |
| FSEG2019 ⚫       | 225.93 ± 125.07        | 0.64 ± 0.39            | 0.36 ± 0.51         | 0.45 ± 0.28            | 0.83 ± 0.07        | 0.34             |
| AgentHerb ⚫      | 34.68 ± 26.82          | 0.08 ± 0.07            | 1.1 ± 0.1           | 0.26 ± 0.17            | 0.26 ± 0.17        | 1.00             |
| Agent33 ⚫        | 13342.01 ± 16011.07    | 0.22 ± 0.26            | 0.99 ± 0.38         | 0.43 ± 0.17            | 0.46 ± 0.16        | 0.88             |
| Sontag ⚫         | 17135.63 ± 22558.8     | 0.45 ± 0.38            | 0.66 ± 0.54         | 0.52 ± 0.24            | 0.70 ± 0.13        | 0.61             |
| AgreeableAgent ⚫ | 18105.12 ± 22793.05    | 0.24 ± 0.29            | 0.92 ± 0.39         | 0.45 ± 0.26            | 0.48 ± 0.26        | 0.86             |
| PonpokoAgent ⚫   | 18432.89 ± 22498.15    | 0.59 ± 0.41            | 0.42 ± 0.54         | 0.48 ± 0.3              | 0.86 ± 0.08        | 0.39             |
| ParsCat2 ⚫       | 14964.65 ± 18228.5     | 0.42 ± 0.38            | 0.70 ± 0.54         | 0.52 ± 0.24            | 0.67 ± 0.15        | 0.63             |

Table 17: Performance of ANESIA-DRL - Ablation Study1 - over domain Grocery (1440 × 2 profiles = 2880 simulations)

| Agent            | $R_{avg}(\downarrow)$ | $P_{avg}(\downarrow)$ | $U_{soc}(\dagger)$ | $U_{total}(\dagger)$ | $U_{soc}(\dagger)$ | $S_R(\dagger)$ |
|------------------|------------------------|------------------------|---------------------|-----------------------|---------------------|-----------------|
| ANESIA-DRL       | 389.41 ± 336.37        | 0.35 ± 0.45            | 1.23 ± 0.69         | 0.64 ± 0.16            | 0.75 ± 0.14        | 0.60             |
| AgentGP ⚫        | 164.79 ± 327.31        | 0.33 ± 0.33            | 1.2 ± 0.51          | 0.68 ± 0.12            | 0.72 ± 0.1          | 0.85             |
| FSEG2019 ⚫       | 336.73 ± 347.68        | 0.26 ± 0.18            | 1.28 ± 0.27         | 0.66 ± 0.11            | 0.67 ± 0.11        | 0.96             |
| AgentHerb ⚫      | 8.78 ± 3.58            | 0.22 ± 0.09            | 1.31 ± 0.12         | 0.53 ± 0.11            | 0.53 ± 0.11        | 1.00             |
| Agent33 ⚫        | 829.95 ± 1243.28       | 0.32 ± 0.24            | 1.22 ± 0.38         | 0.63 ± 0.09            | 0.64 ± 0.09        | 0.92             |
| Sontag ⚫         | 591.79 ± 969.8         | 0.25 ± 0.14            | 1.31 ± 0.21         | 0.64 ± 0.1             | 0.64 ± 0.1         | 0.98             |
| AgreeableAgent ⚫ | 1513.15 ± 1551.39      | 0.32 ± 0.27            | 1.19 ± 0.42         | 0.69 ± 0.11            | 0.71 ± 0.1         | 0.90             |
| PonpokoAgent ⚫   | 1067.18 ± 1318.49      | 0.31 ± 0.29            | 1.2 ± 0.43          | 0.72 ± 0.13            | 0.75 ± 0.11        | 0.89             |
| ParsCat2 ⚫       | 823.48 ± 888.27        | 0.28 ± 0.23            | 1.26 ± 0.35         | 0.67 ± 0.11            | 0.69 ± 0.1         | 0.93             |
Table 18: Performance of ANESIA-DRL - Ablation Study 1 - over domain Fitness (1440 \times 2 profiles = 2880 simulations)

| Agent               | \( R_{\text{avg}}(\uparrow) \) | \( P_{\text{avg}}(\downarrow) \) | \( U_{\text{avg}}(\uparrow) \) | \( U_{\text{ind}}^\text{total}(\uparrow) \) | \( U_{\text{ind}}^\text{social}(\uparrow) \) | \( S_\text{tot}(\uparrow) \) |
|---------------------|-------------------------------|--------------------------------|-----------------|-----------------------------|-----------------------------|-----------------|
| ANESIA-DRL          | 6.5 ± 2.6                     | 0.05 ± 0.06                   | 1.48 ± 0.07     | 0.87 ± 0.15                 | 0.87 ± 0.15                 | 1.00            |
| AgentGP  \( \bullet \) | 307.39 ± 1234.05             | 0.11 ± 0.2                    | 1.32 ± 0.37     | 0.67 ± 0.16                 | 0.68 ± 0.16                 | 0.93            |
| FSEGA2019  \( \bullet \) | 2142.49 ± 3180.88            | 0.09 ± 0.14                   | 1.32 ± 0.25     | 0.77 ± 0.13                 | 0.78 ± 0.12                 | 0.97            |
| AgentHerb  \( \circ \) | 7.36 ± 3.51                   | 0.05 ± 0.05                   | 1.48 ± 0.05     | 0.58 ± 0.1                  | 0.58 ± 0.1                  | 1.00            |
| Agent33  \( \circ \) | 761.68 ± 1289.88              | 0.07 ± 0.05                   | 1.44 ± 0.07     | 0.68 ± 0.12                 | 0.68 ± 0.12                 | 1.00            |
| Sontag  \( \circ \) | 2813.95 ± 5044.51             | 0.07 ± 0.07                   | 1.36 ± 0.14     | 0.78 ± 0.13                 | 0.79 ± 0.13                 | 1.00            |
| AgreeableAgent  \( \circ \) | 0 ± 0                         | 0 ± 0                         | 0 ± 0           | 0 ± 0                       | 0 ± 0                       | 0.00            |
| PonpokoAgent  \( \ast \) | 3993.86 ± 5928.48             | 0.07 ± 0.09                   | 1.3 ± 0.18      | 0.84 ± 0.11                 | 0.84 ± 0.11                 | 0.99            |
| ParsCat2  \( \ast \) | 3173.43 ± 4762.17             | 0.08 ± 0.08                   | 1.32 ± 0.17     | 0.8 ± 0.12                  | 0.8 ± 0.12                  | 0.99            |

Table 19: Performance of ANESIA-DRL - Ablation Study 1 - over domain Flight Booking (1440 \times 2 profiles = 2880 simulations)

| Agent               | \( R_{\text{avg}}(\downarrow) \) | \( P_{\text{avg}}(\downarrow) \) | \( U_{\text{avg}}(\downarrow) \) | \( U_{\text{ind}}^\text{total}(\downarrow) \) | \( U_{\text{ind}}^\text{social}(\downarrow) \) | \( S_\text{tot}(\downarrow) \) |
|---------------------|-------------------------------|--------------------------------|-----------------|-----------------------------|-----------------------------|-----------------|
| ANESIA-DRL          | 8.05 ± 2.6                    | 0.05 ± 0.05                   | 1.51 ± 0.09     | 0.81 ± 0.08                 | 0.81 ± 0.08                 | 1.00            |
| AgentGP  \( \bullet \) | 86.82 ± 151.37               | 0.06 ± 0.03                   | 1.50 ± 0.04     | 0.76 ± 0.07                 | 0.76 ± 0.07                 | 1.00            |
| FSEGA2019  \( \bullet \) | 7584.39 ± 7834.62            | 0.05 ± 0.04                   | 1.51 ± 0.06     | 0.77 ± 0.11                 | 0.77 ± 0.11                 | 1.00            |
| AgentHerb  \( \circ \) | 9.39 ± 3.46                   | 0.06 ± 0.04                   | 1.48 ± 0.05     | 0.6 ± 0.08                  | 0.6 ± 0.08                  | 1.00            |
| Agent33  \( \circ \) | 11817.72 ± 11426.17          | 0.08 ± 0.06                   | 1.48 ± 0.08     | 0.79 ± 0.09                 | 0.79 ± 0.09                 | 1.00            |
| Sontag  \( \circ \) | 8291.78 ± 8988.64             | 0.06 ± 0.05                   | 1.50 ± 0.06     | 0.73 ± 0.11                 | 0.73 ± 0.11                 | 1.00            |
| AgreeableAgent  \( \circ \) | 0 ± 0                         | 0 ± 0                         | 0 ± 0           | 0 ± 0                       | 0 ± 0                       | 0.00            |
| PonpokoAgent  \( \ast \) | 13173.32 ± 12016.88          | 0.05 ± 0.04                   | 1.47 ± 0.05     | 0.81 ± 0.08                 | 0.81 ± 0.08                 | 1.00            |
| ParsCat2  \( \ast \) | 11296.37 ± 10537.68          | 0.07 ± 0.05                   | 1.49 ± 0.06     | 0.77 ± 0.1                  | 0.77 ± 0.1                  | 1.00            |

Table 19: Performance of ANESIA-DRL - Ablation Study 1 - over domain Flight Booking (1440 \times 2 profiles = 2880 simulations)
| Agent          | $R_{avg}(\downarrow)$ | $P_{avg}(\downarrow)$ | $U_{avg}(\uparrow)$ | $U_{total}(\uparrow)$ | $U_{std}(\uparrow)$ | $S_E(\uparrow)$ |
|---------------|------------------------|------------------------|---------------------|-----------------------|---------------------|----------------|
| ANESIA-DRL    | 555.81 ± 532.81        | 0.04 ± 0.16            | 1.27 ± 0.46         | 0.56 ± 0.12           | 0.91 ± 0.16         | 0.27           |
| AgentGP •     | 371.01 ± 177.31        | 0.12 ± 0.18            | 0.58 ± 0.38         | 0.51 ± 0.23           | 0.91 ± 0.27         | 0.77           |
| FSEGA2019 •   | 2714.98 ± 4328.78      | 0.11 ± 0.16            | 0.67 ± 0.37         | 0.66 ± 0.21           | 0.69 ± 0.21         | 0.82           |
| AgentHerb ⊙   | 9.12 ± 6.25            | 0.05 ± 0.06            | 1.13 ± 0.08         | 0.26 ± 0.11           | 0.26 ± 0.11         | 1.00           |
| Agent33 ⊙     | 1850.84 ± 3677.84      | 0.07 ± 0.12            | 0.85 ± 0.34         | 0.42 ± 0.18           | 0.41 ± 0.18         | 0.92           |
| Sontag ⊙      | 2965.81 ± 5008.5       | 0.14 ± 0.19            | 0.63 ± 0.43         | 0.69 ± 0.19           | 0.76 ± 0.17         | 0.73           |
| AgreeableAgent ⊙ | 3933.17 ± 5861.42     | 0.15 ± 0.19            | 0.49 ± 0.37         | 0.67 ± 0.22           | 0.75 ± 0.23         | 0.70           |
| PompokoAgent * | 3909.99 ± 5863.55      | 0.27 ± 0.2             | 0.32 ± 0.4          | 0.65 ± 0.19           | 0.85 ± 0.14         | 0.43           |
| ParsCat2 *    | 2808.13 ± 4315.82      | 0.15 ± 0.19            | 0.61 ± 0.43         | 0.62 ± 0.21           | 0.67 ± 0.24         | 0.72           |

Table 20: Performance of ANESIA-DRL - Ablation Study 1 - over domain Itex (1440 × 2 profiles = 2880 simulations)

| Agent          | $R_{avg}(\downarrow)$ | $P_{avg}(\downarrow)$ | $U_{avg}(\uparrow)$ | $U_{total}(\uparrow)$ | $U_{std}(\uparrow)$ | $S_E(\uparrow)$ |
|---------------|------------------------|------------------------|---------------------|-----------------------|---------------------|----------------|
| ANESIA-DRL    | 381.27 ± 275.45        | 0.04 ± 0.02            | 1.24 ± 0.54         | 0.54 ± 0.3             | 0.82 ± 0.15         | 0.51           |
| AgentGP •     | 542.41 ± 515.26        | 0.24 ± 0.29            | 0.73 ± 0.5          | 0.56 ± 0.27           | 0.7 ± 0.22          | 0.69           |
| FSEGA2019 •   | 806.26 ± 1067.19       | 0.08 ± 0.19            | 1.03 ± 0.34         | 0.6 ± 0.24            | 0.64 ± 0.22         | 0.91           |
| AgentHerb ⊙   | 6.44 ± 5.1             | 0.04 ± 0.05            | 1.21 ± 0.07         | 0.37 ± 0.14           | 0.37 ± 0.14         | 1.00           |
| Agent33 ⊙     | 289.54 ± 402.6         | 0.05 ± 0.09            | 1.16 ± 0.18         | 0.44 ± 0.18           | 0.44 ± 0.18         | 0.98           |
| Sontag ⊙      | 881.04 ± 1273.89       | 0.07 ± 0.19            | 1.06 ± 0.36         | 0.61 ± 0.24           | 0.65 ± 0.22         | 0.91           |
| AgreeableAgent ⊙ | 1398.88 ± 1655.48     | 0.11 ± 0.22            | 0.92 ± 0.37         | 0.69 ± 0.27           | 0.76 ± 0.22         | 0.87           |
| PompokoAgent * | 1190.43 ± 1689.85      | 0.17 ± 0.11            | 0.91 ± 0.43         | 0.68 ± 0.24           | 0.77 ± 0.16         | 0.83           |
| ParsCat2 *    | 907.87 ± 1153.59       | 0.08 ± 0.2             | 1.03 ± 0.36         | 0.61 ± 0.25           | 0.65 ± 0.23         | 0.90           |

Table 21: Performance of ANESIA-DRL - Ablation Study 1 - over domain Outfit (1440 × 2 profiles = 2880 simulations)
### Table 22: Performance of ANESIA-Random - Ablation Study 2 - over domain AIRPORT (1440 × 2 profiles = 2880 simulations)

| Agent                | $R_{avg}(\%)$       | $P_{avg}(\%)$       | $U_{soc}(\%)$       | $U_{total}(\%)$      | $U_{text}(\%)$      | $S_D(\%)$       |
|----------------------|---------------------|---------------------|---------------------|----------------------|---------------------|----------------|
| ANESIA-rand          | 119.3 ± 125.27      | 0.2 ± 0.26          | 1.38 ± 0.38         | 0.6 ± 0.2            | 0.81 ± 0.2          | 0.95           |
| AgentGP ⊗            | 127.66 ± 116.32     | 0.04 ± 0.14         | 1.48 ± 0.21         | 0.64 ± 0.12          | 0.65 ± 0.12         | 0.99           |
| FSEGA2019 ⊗          | 439.89 ± 636.24     | 0.06 ± 0.14         | 1.47 ± 0.18         | 0.75 ± 0.16          | 0.75 ± 0.16         | 1.00           |
| AgentHerb ⊗          | 10.64 ± 7.45        | 0.2 ± 0.22          | 1.25 ± 0.24         | 0.48 ± 0.22          | 0.48 ± 0.22         | 1.00           |
| Agent33 ⊗            | 374.62 ± 500.5      | 0.2 ± 0.24          | 1.23 ± 0.35         | 0.54 ± 0.16          | 0.54 ± 0.16         | 0.99           |
| Sontag ⊗             | 434.54 ± 488.25     | 0.11 ± 0.24         | 1.38 ± 0.34         | 0.73 ± 0.19          | 0.74 ± 0.19         | 0.97           |
| AgreeableAgent ⊗     | 673.59 ± 705.79     | 0.13 ± 0.27         | 1.34 ± 0.37         | 0.82 ± 0.19          | 0.83 ± 0.19         | 0.96           |
| PompokoAgent *        | 688.06 ± 648.93     | 0.18 ± 0.31         | 1.29 ± 0.44         | 0.82 ± 0.14          | 0.85 ± 0.1          | 0.92           |
| ParsCat2 *            | 492.9 ± 539.28      | 0.09 ± 0.17         | 1.42 ± 0.25         | 0.75 ± 0.19          | 0.75 ± 0.19         | 1.00           |

### Table 23: Performance of ANESIA-Random - Ablation Study 2 - over domain Camera (1440 × 2 profiles = 2880 simulations)

| Agent                | $R_{avg}(\%)$       | $P_{avg}(\%)$       | $U_{soc}(\%)$       | $U_{total}(\%)$      | $U_{text}(\%)$      | $S_D(\%)$       |
|----------------------|---------------------|---------------------|---------------------|----------------------|---------------------|----------------|
| ANESIA-rand          | 117.9 ± 82.03       | 0.2 ± 0.22          | 1.19 ± 0.54         | 0.58 ± 0.23          | 0.79 ± 0.14         | 0.73           |
| AgentGP ⊗            | 98.23 ± 88.77       | 0.04 ± 0.10         | 1.17 ± 0.34         | 0.72 ± 0.18          | 0.74 ± 0.17         | 0.98           |
| FSEGA2019 ⊗          | 365.7 ± 388.48      | 0.06 ± 0.09         | 1.09 ± 0.32         | 0.74 ± 0.19          | 0.75 ± 0.18         | 0.98           |
| AgentHerb ⊗          | 3.83 ± 1.39         | 0.02 ± 0.05         | 1.52 ± 0.13         | 0.60 ± 0.13          | 0.60 ± 0.13         | 1.00           |
| Agent33 ⊗            | 128.23 ± 215.83     | 0.06 ± 0.09         | 1.33 ± 0.19         | 0.61 ± 0.15          | 0.61 ± 0.15         | 1.00           |
| Sontag ⊗             | 363.22 ± 387.03     | 0.06 ± 0.12         | 1.09 ± 0.36         | 0.74 ± 0.16          | 0.77 ± 0.13         | 0.96           |
| AgreeableAgent ⊗     | 516.15 ± 483.34     | 0.05 ± 0.1          | 0.94 ± 0.36         | 0.82 ± 0.18          | 0.83 ± 0.15         | 0.97           |
| PompokoAgent *        | 516.42 ± 483.8      | 0.08 ± 0.14         | 0.92 ± 0.38         | 0.80 ± 0.18          | 0.84 ± 0.09         | 0.93           |
| ParsCat2 *            | 417.44 ± 424.29     | 0.08 ± 0.1          | 1.05 ± 0.33         | 0.76 ± 0.16          | 0.77 ± 0.14         | 0.98           |
Table 25: Performance of ANESIA - Ablation Study2 - over domain Energy (1440 × 2 profiles = 2880 simulations)

| Energy Domain B = 5% of Ω | Agent   | $R_{avg}(\downarrow)$ | $P_{avg}(\downarrow)$ | $U_{soc}(\uparrow)$ | $U_{mid}^{total}(\uparrow)$ | $U_{mid}^{avg}(\uparrow)$ | $S_{soc}(\uparrow)$ |
|---------------------------|---------|------------------------|------------------------|---------------------|-----------------------------|-----------------------------|------------------|
| ANESIA-rand               | 82.44 ± 789.03 | 0.19 ± 0.21            | 1.11 ± 0.29            | 0.45 ± 0.22         | 0.4 ± 0.22                  | 0.94                   |
| AgentHerb ○              | 35.12 ± 25.49 | 0.08 ± 0.08            | 1.08 ± 0.1             | 0.25 ± 0.16         | 0.25 ± 0.16                 | 1.00                   |
| Agent33 ○                | 7123.76 ± 9819.55 | 0.15 ± 0.12            | 1.10 ± 0.18            | 0.48 ± 0.17         | 0.48 ± 0.17                 | 0.98                   |
| Sontag ○                 | 9379.17 ± 12799.92 | 0.37 ± 0.36            | 0.77 ± 0.51            | 0.57 ± 0.23         | 0.71 ± 0.12                 | 0.71                   |
| AgreeableAgent ○         | 10773.89 ± 13829.31 | 0.23 ± 0.26            | 0.92 ± 0.39            | 0.46 ± 0.26         | 0.5 ± 0.27                  | 0.86                   |
| PonpokoAgent ○           | 10507.22 ± 13470.76 | 0.52 ± 0.42            | 0.51 ± 0.54            | 0.53 ± 0.3          | 0.84 ± 0.1                  | 0.47                   |
| ParsCat2 *               | 7395.98 ± 9537.85 | 0.37 ± 0.37            | 0.75 ± 0.51            | 0.55 ± 0.24         | 0.69 ± 0.17                 | 0.69                   |

| Energy Domain B = 10% of Ω | Agent   | $R_{avg}(\downarrow)$ | $P_{avg}(\downarrow)$ | $U_{soc}(\uparrow)$ | $U_{mid}^{total}(\uparrow)$ | $U_{mid}^{avg}(\uparrow)$ | $S_{soc}(\uparrow)$ |
|---------------------------|---------|------------------------|------------------------|---------------------|-----------------------------|-----------------------------|------------------|
| ANESIA-rand               | 796.79 ± 817.44 | 0.08 ± 0.09            | 1.14 ± 0.27            | 0.5 ± 0.21          | 0.51 ± 0.21                 | 0.95                   |
| AgentHerb ○              | 35.26 ± 26.87 | 0.08 ± 0.08            | 1.10 ± 0.11            | 0.26 ± 0.16         | 0.26 ± 0.16                 | 1.00                   |
| Agent33 ○                | 6776.28 ± 8751.38 | 0.16 ± 0.17            | 1.08 ± 0.25            | 0.46 ± 0.17         | 0.47 ± 0.16                 | 0.96                   |
| Sontag ○                 | 8960.3 ± 12934.01 | 0.36 ± 0.36            | 0.79 ± 0.5             | 0.57 ± 0.23         | 0.69 ± 0.13                 | 0.72                   |
| AgreeableAgent ○         | 9835.89 ± 13329.52 | 0.2 ± 0.26             | 0.97 ± 0.35            | 0.49 ± 0.26         | 0.52 ± 0.27                 | 0.89                   |
| PonpokoAgent ○           | 9539.13 ± 12556.79 | 0.54 ± 0.41            | 0.49 ± 0.55            | 0.52 ± 0.3          | 0.84 ± 0.09                 | 0.46                   |
| ParsCat2 *               | 7983.96 ± 10401.7 | 0.38 ± 0.36            | 0.75 ± 0.51            | 0.54 ± 0.23         | 0.67 ± 0.15                 | 0.69                   |

Table 24: Performance of ANESIA-Random - Ablation Study2 - over domain Energy (1440 × 2 profiles = 2880 simulations)

| Grocery Domain B = 5% of Ω | Agent   | $R_{avg}(\downarrow)$ | $P_{avg}(\downarrow)$ | $U_{soc}(\uparrow)$ | $U_{mid}^{total}(\uparrow)$ | $U_{mid}^{avg}(\uparrow)$ | $S_{soc}(\uparrow)$ |
|---------------------------|---------|------------------------|------------------------|---------------------|-----------------------------|-----------------------------|------------------|
| ANESIA-rand               | 237.6 ± 225.72 | 0.21 ± 0.24            | 1.27 ± 0.45            | 0.64 ± 0.28         | 0.73 ± 0.14                 | 0.87                   |
| AgentHerb ○              | 4.56 ± 2.37 | 0.26 ± 0.07            | 1.24 ± 0.14            | 0.51 ± 0.15         | 0.51 ± 0.15                 | 1.00                   |
| Agent33 ○                | 90.53 ± 97.13 | 0.24 ± 0.07            | 1.25 ± 0.14            | 0.57 ± 0.16         | 0.57 ± 0.16                 | 1.00                   |
| Sontag ○                 | 363.54 ± 669.3 | 0.21 ± 0.08            | 1.25 ± 0.17            | 0.66 ± 0.14         | 0.66 ± 0.13                 | 0.99                   |
| AgreeableAgent ○         | 808.19 ± 812.66 | 0.23 ± 0.11            | 1.04 ± 0.19            | 0.68 ± 0.13         | 0.69 ± 0.09                 | 0.98                   |
| PonpokoAgent ○           | 441.17 ± 605.81 | 0.22 ± 0.12            | 1.20 ± 0.24            | 0.68 ± 0.15         | 0.70 ± 0.1                  | 0.97                   |
| ParsCat2 *               | 313.02 ± 395.48 | 0.22 ± 0.12            | 1.23 ± 0.22            | 0.66 ± 0.16         | 0.67 ± 0.13                 | 0.98                   |

| Grocery Domain B = 10% of Ω | Agent   | $R_{avg}(\downarrow)$ | $P_{avg}(\downarrow)$ | $U_{soc}(\uparrow)$ | $U_{mid}^{total}(\uparrow)$ | $U_{mid}^{avg}(\uparrow)$ | $S_{soc}(\uparrow)$ |
|---------------------------|---------|------------------------|------------------------|---------------------|-----------------------------|-----------------------------|------------------|
| ANESIA-rand               | 262.29 ± 255.59 | 0.22 ± 0.22            | 1.28 ± 0.36            | 0.67 ± 0.16         | 0.68 ± 0.16                 | 0.95                   |
| AgentHerb ○              | 8.42 ± 3.82 | 0.22 ± 0.08            | 1.31 ± 0.12            | 0.54 ± 0.1          | 0.54 ± 0.1                  | 1.00                   |
| Agent33 ○                | 531.96 ± 769.85 | 0.27 ± 0.14            | 1.29 ± 0.22            | 0.63 ± 0.09         | 0.63 ± 0.09                 | 0.98                   |
| Sontag ○                 | 392.43 ± 571.41 | 0.23 ± 0.1             | 1.33 ± 0.15            | 0.65 ± 0.11         | 0.65 ± 0.11                 | 1.00                   |
| AgreeableAgent ○         | 1090.66 ± 1101.45 | 0.24 ± 0.12            | 1.31 ± 0.18            | 0.71 ± 0.01         | 0.72 ± 0.09                 | 0.99                   |
| PonpokoAgent ○           | 769.14 ± 919.8 | 0.24 ± 0.13            | 1.32 ± 0.19            | 0.74 ± 0.1          | 0.74 ± 0.1                  | 0.98                   |
| ParsCat2 *               | 598.63 ± 621.81 | 0.25 ± 0.1             | 1.31 ± 0.16            | 0.69 ± 0.09         | 0.69 ± 0.09                 | 0.99                   |

Table 25: Performance of ANESIA-Random - Ablation Study2 - over domain Grocery (1440 × 2 profiles = 2880 simulations)
| Agent            | $R_{avg}(\downarrow)$ | $P_{avg}(\downarrow)$ | $U_{soc}(\uparrow)$ | $U_{total}(\uparrow)$ | $U_{avg}(\uparrow)$ | $S_{soc}(\uparrow)$ |
|------------------|------------------------|------------------------|---------------------|------------------------|---------------------|------------------|
| ANESIA-rand      | 7.11 ± 2.59            | 0.05 ± 0.07            | 1.49 ± 0.08         | 0.89 ± 0.13            | 0.59 ± 0.13         | 1.00             |
| AgentGP          | 577.86 ± 1122.43       | 0.19 ± 0.31            | 1.16 ± 0.56         | 0.64 ± 0.16            | 0.67 ± 0.16         | 0.82             |
| FSEGAv2019       | 1476.17 ± 1984.41      | 0.1 ± 0.16             | 1.3 ± 0.29          | 0.77 ± 0.13            | 0.78 ± 0.12         | 0.96             |

| Agent            | $R_{avg}(\downarrow)$ | $P_{avg}(\downarrow)$ | $U_{soc}(\uparrow)$ | $U_{total}(\uparrow)$ | $U_{avg}(\uparrow)$ | $S_{soc}(\uparrow)$ |
|------------------|------------------------|------------------------|---------------------|------------------------|---------------------|------------------|
| AgentHerb        | 7.23 ± 3.22            | 0.04 ± 0.05            | 1.49 ± 0.05         | 0.58 ± 0.1             | 0.58 ± 0.1          | 1.00             |
| Agent33          | 569.85 ± 956.24        | 0.07 ± 0.05            | 1.43 ± 0.07         | 0.69 ± 0.12            | 0.69 ± 0.12         | 0.97             |
| Sontag           | 1708.57 ± 2728.7       | 0.09 ± 0.14            | 1.33 ± 0.26         | 0.78 ± 0.14            | 0.78 ± 0.13         | 0.97             |
| AgreeableAgent   | 0 ± 0                  | 0 ± 0                  | 0 ± 0               | 0 ± 0                  | 0 ± 0               | 0.00             |
| PompokoAgent     | 2805.01 ± 4277.85      | 0.09 ± 0.16            | 1.26 ± 0.28         | 0.83 ± 0.13            | 0.84 ± 0.11         | 0.96             |
| ParsCat2         | 2641.97 ± 4328.13      | 0.11 ± 0.16            | 1.27 ± 0.29         | 0.79 ± 0.13            | 0.80 ± 0.12         | 0.96             |

Table 26: Performance of ANESIA-Random - Ablation Study2 - over domain Fitness (1440 × 2 profiles = 2880 simulations)

| Agent            | $R_{avg}(\downarrow)$ | $P_{avg}(\downarrow)$ | $U_{soc}(\uparrow)$ | $U_{total}(\uparrow)$ | $U_{avg}(\uparrow)$ | $S_{soc}(\uparrow)$ |
|------------------|------------------------|------------------------|---------------------|------------------------|---------------------|------------------|
| ANESIA-rand      | 7.88 ± 2.6             | 0.08 ± 0.05            | 1.48 ± 0.08         | 0.77 ± 0.09            | 0.77 ± 0.09         | 1.00             |
| AgentGP          | 121.18 ± 359.01        | 0.08 ± 0.12            | 1.48 ± 0.17         | 0.76 ± 0.08            | 0.76 ± 0.06         | 0.99             |
| FSEGAv2019       | 2461.25 ± 3791.92      | 0.05 ± 0.04            | 1.51 ± 0.06         | 0.77 ± 0.11            | 0.77 ± 0.11         | 1.00             |

| Agent            | $R_{avg}(\downarrow)$ | $P_{avg}(\downarrow)$ | $U_{soc}(\uparrow)$ | $U_{total}(\uparrow)$ | $U_{avg}(\uparrow)$ | $S_{soc}(\uparrow)$ |
|------------------|------------------------|------------------------|---------------------|------------------------|---------------------|------------------|
| AgentHerb        | 9.57 ± 3.75            | 0.06 ± 0.03            | 1.48 ± 0.05         | 0.6 ± 0.09             | 0.6 ± 0.09          | 1.00             |
| Agent33          | 4299.9 ± 6395.93       | 0.09 ± 0.13            | 1.46 ± 0.18         | 0.78 ± 0.11            | 0.79 ± 0.09         | 0.99             |
| Sontag           | 3223.29 ± 6109.35      | 0.17 ± 0.05            | 1.49 ± 0.07         | 0.73 ± 0.11            | 0.73 ± 0.11         | 1.00             |
| AgreeableAgent   | 0 ± 0                  | 0 ± 0                  | 0 ± 0               | 0 ± 0                  | 0 ± 0               | 0.00             |
| PompokoAgent     | 5035.09 ± 7372.96      | 0.08 ± 0.04            | 1.47 ± 0.05         | 0.8 ± 0.08             | 0.50 ± 0.08         | 1.00             |
| ParsCat2         | 4005.65 ± 5637.52      | 0.07 ± 0.05            | 1.49 ± 0.07         | 0.77 ± 0.11            | 0.77 ± 0.11         | 1.00             |

Table 27: Performance of ANESIA-Random - Ablation Study2 - over domain Flight Booking (1440 × 2 profiles = 2880 simulations)
Table 29: Performance of ANESIA-Random - Ablation Study2 - over domain Outfit (1440 × 2 profiles = 2880 simulations)

| Agent                  | $R_{\text{avg}}(\%)$ | $P_{\text{avg}}(\%)$ | $U_{\text{avg}}(\%)$ | $U_{\text{total}}(\%)$ | $U_{\text{avg}}(\%)$ | $S_{\text{avg}}(\%)$ |
|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|
| ANESIA-rand            | 6.3 ± 2.92             | 6.3 ± 2.00             | 6.3 ± 2.00             | 6.3 ± 2.00             | 6.3 ± 2.00             | 6.3 ± 2.00             |
| AgentGP                | 490.14 ± 513.72        | 0.14 ± 0.24            | 0.9 ± 0.42             | 0.65 ± 0.26            | 0.73 ± 0.21            | 0.83 ± 0.08            |
| FSEGA2019              | 475.94 ± 510.89        | 0.14 ± 0.24            | 0.9 ± 0.42             | 0.65 ± 0.26            | 0.73 ± 0.21            | 0.83 ± 0.08            |
| AgentHerb              | 6.3 ± 2.92             | 6.3 ± 2.00             | 6.3 ± 2.00             | 6.3 ± 2.00             | 6.3 ± 2.00             | 6.3 ± 2.00             |
| Agent33                | 504.73 ± 674.86        | 0.05 ± 0.09            | 1.16 ± 0.17            | 0.43 ± 0.18            | 0.44 ± 0.18            | 0.99 ± 0.08            |
| Sontag                | 1754.89 ± 2934.17      | 0.05 ± 0.13            | 1.12 ± 0.26            | 0.63 ± 0.22            | 0.65 ± 0.21            | 0.96 ± 0.08            |
| AgreeableAgent         | 3252.78 ± 4395.75      | 0.07 ± 0.18            | 0.98 ± 0.31            | 0.73 ± 0.24            | 0.77 ± 0.2            | 0.92 ± 0.08            |
| PompokoAgent           | 2817.47 ± 4135.53      | 0.08 ± 0.19            | 1.01 ± 0.34            | 0.72 ± 0.21            | 0.76 ± 0.16            | 0.91 ± 0.08            |
| ParsCat2               | 1782.24 ± 2686.54      | 0.04 ± 0.13            | 1.11 ± 0.24            | 0.64 ± 0.23            | 0.66 ± 0.22            | 0.96 ± 0.08            |

Table 28: Performance of ANESIA-Random - Ablation Study2 - over domain IteX (1440 × 2 profiles = 2880 simulations)

| Agent                  | $R_{\text{avg}}(\%)$ | $P_{\text{avg}}(\%)$ | $U_{\text{avg}}(\%)$ | $U_{\text{total}}(\%)$ | $U_{\text{avg}}(\%)$ | $S_{\text{avg}}(\%)$ |
|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|
| ANESIA-rand            | 632.74 ± 580.27        | 0.12 ± 0.27            | 1.19 ± 0.47            | 0.60 ± 0.26            | 0.75 ± 0.19            | 0.75 ± 0.08            |
| AgentGP                | 490.14 ± 513.72        | 0.14 ± 0.24            | 0.9 ± 0.42             | 0.65 ± 0.26            | 0.73 ± 0.21            | 0.83 ± 0.08            |
| FSEGA2019              | 475.94 ± 510.89        | 0.14 ± 0.24            | 0.9 ± 0.42             | 0.65 ± 0.26            | 0.73 ± 0.21            | 0.83 ± 0.08            |
| AgentHerb              | 6.3 ± 2.92             | 6.3 ± 2.00             | 6.3 ± 2.00             | 6.3 ± 2.00             | 6.3 ± 2.00             | 6.3 ± 2.00             |
| Agent33                | 504.73 ± 674.86        | 0.05 ± 0.09            | 1.16 ± 0.17            | 0.43 ± 0.18            | 0.44 ± 0.18            | 0.99 ± 0.08            |
| Sontag                | 1754.89 ± 2934.17      | 0.05 ± 0.13            | 1.12 ± 0.26            | 0.63 ± 0.22            | 0.65 ± 0.21            | 0.96 ± 0.08            |
| AgreeableAgent         | 3252.78 ± 4395.75      | 0.07 ± 0.18            | 0.98 ± 0.31            | 0.73 ± 0.24            | 0.77 ± 0.2            | 0.92 ± 0.08            |
| PompokoAgent           | 2817.47 ± 4135.53      | 0.08 ± 0.19            | 1.01 ± 0.34            | 0.72 ± 0.21            | 0.76 ± 0.16            | 0.91 ± 0.08            |
| ParsCat2               | 1782.24 ± 2686.54      | 0.04 ± 0.13            | 1.11 ± 0.24            | 0.64 ± 0.23            | 0.66 ± 0.22            | 0.96 ± 0.08            |

Table 29: Performance of ANESIA-Random - Ablation Study2 - over domain Outfit (1440 × 2 profiles = 2880 simulations)