Creating Intelligent Agents: Combining Agent-Based Modeling with Machine Learning

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Abstract Over the last two decades, with advances in computational availability and power, we have seen a rapid increase in the development and use of Machine Learning (ML) solutions applied to a wide range of applications including their use within agent-based models. However, little attention has been given to how different ML methods alter the simulation results. Within this paper, we discuss how ML methods have been utilized within agent-based models and explore how different methods affect the results. We do this by extending the Sugarscape model to include three ML methods (evolutionary computing, and two reinforcement learning algorithms (i.e., Q-Learning, and State → Action → Reward → State → Action (SARSA)). We pit these ML methods against each other and the normal functioning of the rule-based method (Rule M) in pairwise combat. Our results demonstrate ML methods can be integrated into agent-based models, that learning does not always mean better results, and that agent attributes considered important to the modeler might not be to the agent. Our paper's contribution to the field of agent-based modeling is not only to show how previous researchers have used ML but also to directly compare and contrast how different ML methods used in the same model impact the simulation outcome. Since this is rarely discussed, doing so will help bring awareness to researchers who are considering using intelligent agents to improve their models.

Keywords Agent-based modeling · Evolutionary computing · Machine learning · Reinforcement learning · Sugarscape

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1 Introduction

Advances in computational availability and power have permitted a rapid increase in the development and use of machine learning (ML) solutions in a wide variety of applications (Batty et al. 2012). With this growth there is growing interest utilizing ML within agent-based models as it has the potential to move from simple agents to complex ones (see Crooks et al. 2020; Rand 2006). Broadly speaking, agent-based modeling can be considered to have three major steps: (1) design of the model, (2) execution of the model, and (3) evaluation of the model. Machine learning techniques have been applied to all three of these phases (see Abdulkareem et al. 2019). For example, Kavak et al. (2018) used ML to derive parameter values for an agent-based model such as human mobility. Others have used ML during the running of the model, allowing agents to learn from past experiences and make more informed decisions via reinforcement learning (Ramchandani et al. 2017). With respect to using ML algorithms to analyze model outputs, Heppenstall et al. (2007) used a genetic algorithm to validate outcomes of an agent-based model which simulates the retail petrol market.

In the ML community at large, it is common to compare different approaches and take the one that gives the best result (e.g., Yuan et al. 2019), but this is not the case within the social simulation community. While there is growing interest in ML within the agent-based modeling community, little has been written with respect to why one ML method was chosen over another, or how the simulation results might be different if different ML methods are used. The purpose of this paper is therefore to demonstrate the integration of three machine learning methods into a well-known agent based model (i.e., the Sugarscape model (Epstein and Axtell 1996)) and to demonstrate how different methods alter the outcomes of a simulation. In the remainder of this paper, we first provide a brief overview of Machine Learning (ML) and its utilization within agent-based models (Sect. 2) before presenting our methodology in Sect. 3. Section 4 shows the results of different ML methods and Sect. 5 concludes the paper with some thoughts on future directions on using machine learning with agent-based models.

2 Background

Machine learning, a subfield of artificial intelligence, is a large subject area and to cover all types of methods is beyond the scope of this paper (interested readers are referred to Russell and Norvig 2016). Therefore, this paper focuses on two major types of ML: Evolutionary Computing (EC), and Reinforcement Learning (RL). Scope is further limited to agent-based models that support social science research and enhance the capability of individual agents during the execution of the model. In contrast, ML used specifically to optimize model parameters (e.g., Junges and Klügl 2011; Ma et al. 2014) or explore model outputs (e.g., Heppenstall et al. 2007) are not considered within this paper since these processes enhance the modeler rather than the model.

Our rationale for focusing on learning within the agents echoes that of Samuel (1959) who coined the phrase "*Machine Learning*" for a computer program capable of improving itself "*to play a better game of checkers than can be played by the person who wrote the program.*" The ability to exceed its original program is a key facet of ML. Feedback to decisions made by the program, based on the program's observations of its environment, allows it to adjust its internal representations to make better future decisions (Russell and Norvig 2016). Thus, the computer improves its ability to accomplish a task or achieve a goal.

One key element of agent-based models is that of the agent's ability to learn from past decisions and improve their decision making. Many agent-based models utilize simple rules (e.g. Crooks 2010; Schelling 1971) that are capable of creating complex, system level results. The simple rules, however, do not always provide the desired results. For example, Macy and Flache (2002) stated that the focus of modeling cooperation might need to move away from population level dynamics to, "*cognitive dynamics at the level of the individual.*" Also Devezer et al. (2019) noted that a limitation of their agent-based model was the inability of their simple agents to learn and remember previous decisions. To correct this, agents may need a capability to create dynamic rules that adapt to individual experiences: a memory of previous decisions and their consequences. Without experience to guide them, agents may be reduced to random decisions or encounters. People largely do not conduct themselves randomly (Kennedy 2012), so incorporating experiences may lead to more accurate social science models.

In order for agents to learn we can turn to two of the most widely used ML methods, that of EC and RL. With respect to EC, probably the most well-known subclass is that of Genetic Algorithms (GAs). GAs were first introduced by Holland (1975) and provide a means for the future agent behaviors to change when successful agents share their knowledge, represented as a feature set (genes), with their offspring. Offspring agents are created by selecting successful parents, combining portions of the parent's features, and then randomly changing a small percentage of the offspring's features (Reproduction, Crossover, and Mutation). Over time the agent Collective moves toward an optimal solution. Holland's (1975) original structures have been adapted from a variety of fields as shown in Table 1. Another subclass of EC is Genetic Programming (GP) which was introduced by Koza (1992) and is similar to GA, the focus, however, is on code segments that are available for reproduction, crossover, and mutation rather than agent features (i.e., attributes). Holland (1975) and Koza's (1992) use of the word "genetic" to describe their ideas show the link to biological evolution. Social scientists first questioned whether it was valid to employ biological evolution concepts to social processes (see Chattoe-Brown 1998). This initial skepticism has been overcome and EC has been used within agent-based models to study a variety of social problems ranging from economics, social dynamics to that of teamwork (see Appendix A and Table A.1 and Revay and Cioffi-Revilla (2018) for further details).

Table 1 A historical look at the fields of study utilizing adaptive structures (operators + structure) and performance measures which inspired the beginning of GA study (adapted from Holland, 1975)

Field	Structure	Operators (Processes)	Performance Measure
Genetics	Chromosomes	Mutation, recombination, etc	Fitness
Economic planning	Mixes of goods	Production activities	Utility
Control	Policies	Bayes's rule, successive approximation, etc	Error functions
Physiological psychology	Cell assemblies	Synapse modification	Performance rate
Game theory	Strategies	Rules for iterative approximation of optimal strategy	Payoff
Artificial Intelligence	Programs	"Learning" rates	Comparative efficiency

As noted above, another widely used approach in ML is RL, which originated from behavioral psychology and neuroscience (Sutton and Barto, 2018). RL provides a framework for agents to learn by sequential interaction with their environment and other agents in much the same way humans learn. These agents develop decision-making sequences that maximize a reward for a future goal. The frameworks do not require any prior knowledge, although such knowledge is sometimes included (e.g., the transfer of agent knowledge between models (Takadama et al. 2008)), and agents can learn by playing against themselves (e.g. a Markov game with teams of competing agents (Nowé et al. 2006)). Agents decide to move from a current state to a new state using a type of learned Markov decision process (Sutton and Barto 2018). Similar to ML, RL is not a single methodology, but encompasses a number of approaches.n

Table 2 provides examples of RL types that we have found to be used in agent-based modeling (see Appendix B for more details), along with abbreviations used in this paper. This is not, however, a full list of RL methods, and such a list and detailed explanation of these are beyond the scope of this paper. We refer readers to Sutton and Barto (2018) for further examples. As with EC, RL has gained interest in the agent-based modeling community to explore a wide variety of applications from economics to the social dynamics of societies (examples of which are presented in Table B.1).

Table 2 Examples of different reinforcement learning types

Reinforcement Learning Type	Description	References
Bush–Mosteller (BM)	A type of statistical learning where a predictive function is derived from data	Bush and Mosteller (1955)
Learning Automata (LA)	Simple algorithm operating in a stochastic environment where agents can improve their actions during operation	Narendra and Thathachar (1974)
Q-Learning (QL)	Learns a policy, expressed as a matrix of values for states and actions, thus telling an agent what to do in different circumstances. It does not require a model of the problem to be solved. (State → Action → Reward)	Watkins (1989)
State → Action → Reward → State → Action (SARSA)	Extends Q-Learning by also considering the future selected state-action. Uses a model it builds	Rummery and Niranjan (1994)
Temporal-Difference (TD)	Learns from experience without an environmental model and updates estimates before final outcome is known	Sutton (1988)

3 Methodology

In order to demonstrate the differences between rule-based and learning agents, and show how learning agents can be integrated into an agent-based model, we adapted the "*Sugarscape 2 Constant Growback*" (Li and Wilensky 2009) model, which is included in the NetLogo (Wilensky 1999) models library. Our rationale for choosing this model was that it is well known within the social sciences, and the purpose of this paper was not to solve or explore social issues, but to test the usability of EC and RL within an agent-based model. Using a well-known model seemed the logical choice. Sugarscape (Epstein and Axtell 1996) has been used to demonstrate migration, trade, wealth inequality, disease processes, sex, culture, and conflict. It is on conflict, in the form of combat that we focus on within this paper as will be shown with the results in Sect. 4. Within the Sugarscape model there are two groups of agents (i.e., red and blue), where individual agents are allowed to move to the nearest unoccupied location with the most sugar and consume sugar at the location, metabolize sugar, and die if it runs out of sugar. Our model adds combat with agents that can attack and retreat. The basic logic of the model is presented in Fig. 1 while Table 3 specifies the differences between the "original" Sugarscape model and the one presented in this paper. Much of the model is similar to the original model but with the additions to support EC and RL that are highlighted in Table 4. Due to

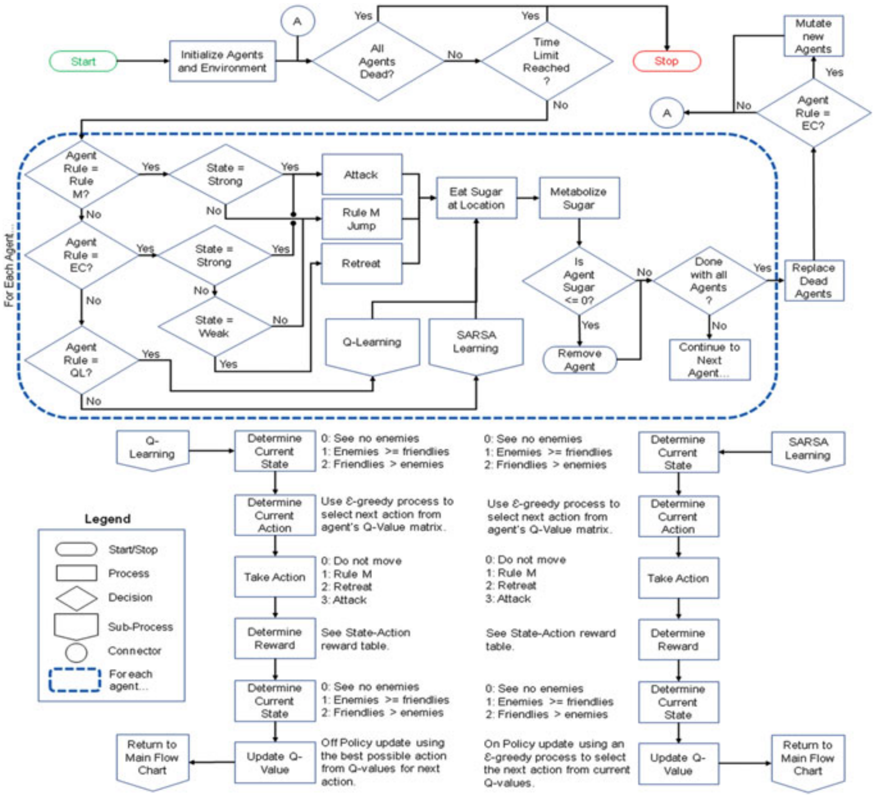

Fig. 1 Model execution flowchart

word limitations, readers are referred to supplementary material provided at https://tinyurl.com/ML-Agents. At this link the model presented in this paper along with a full description of it following the Overview, Design concepts, and Details (ODD, Grimm et al. 2020) protocol can be found. We do this to allow others to replicate the results and adapt the ML methods for their own applications if they so desire.

As the focus of this paper is to demonstrate, compare, and contrast different ML methods for agent learning, we now provide a brief description of the ML utilized within this paper, along with the original model's rule-based method, Rule M. We have created agent learning types (i.e., Q-Learning, SARSA, and EC) and the actions that can be taken are shown in Fig. 1. Figure 1 also shows how these sub-models are positioned in the process flow and below we provide a brief discussion of each one (further details can be found in the online supplementary material):

- **Rule M** type agents use explicit knowledge in the form of a priori rules imposed by the modeler to determine actions (i.e., as in the original model) given its state. These agents do not learn.

Table 3 Differences between the "original" Sugarscape and the ML models developed for this paper

Attribute	Original base model	ML model	Attribute type
Collectives (Breeds)	No	Group A and Group B	Fixed
Discount Rate (Gamma)	No	0.9	Hyper Parameter
Epsilon-Greedy	No	$\epsilon = \frac{1}{1+e^{\frac{t-5000}{1000}}}$	Fixed
Evolutionary computing	No	Yes	Rule
Geographic sugar distribution	Fixed	Fixed	Fixed
Grow back rate (Sugar)	1	[0.1,1.0], Increment of 0.1	Parameter
Initial population	[10,1000], Increment of 10	[1,400], Increment of 1	Parameter
Initial sugar per agent	[5,25], Increment of 1	[5,25], Increment of 1	Parameter
Learning rate (Lambda)	No	0.8	Hyper Parameter
Metabolism	[1,4], Increment of 1	[1,4], Increment of 1	Parameter
Q-learning	No	Yes	Rule
Reward	No	Yes	Fixed
Rule M	Yes	Yes	Rule
Rule R	No	Yes	Rule
SARSA learning	No	Yes	Rule
Time limit	No	20,001	Fixed
Vision	[1,6], Increment of 1	[1,6], Increment of 1	Parameter
Vision neighborhood	von Neumann	von Neumann	Fixed

- **EC type** agents use explicit knowledge in the form of a priori rules imposed by the modeler to determine actions given its state. The EC agents learn as a Collective (i.e., red or blue groups) using evolutionary computing (Holland 1975). As EC agents die and are replaced, the new agent's metabolism and vision attribute values are initialized based on those agents in their Collective that have the most wealth rather than a random value. The mean vision and metabolism attributes for the Collective converge to a local maximum that represents a best choice for wealth accumulation.
- **Q-Learning and SARSA** type agents uses reinforcement learning (Sutton 1988; Sutton and Barto 2018) to gather tacit knowledge over time and store their experience in a Q-Value (Quality Value) matrix. Initially, these agents explore their

Table 4 List of model attributes and their descriptions

Attribute	Description
Collectives (Breeds)	Agents are divided into two groups that can compete with each other
Discount rate (Gamma)	In reinforcement learning this value diminishes the impact of future rewards
Epsilon-Greedy	In reinforcement learning, this changes the probability of exploration versus exploitation of time
Evolutionary computing	A rule that creates a new agent via crossover of the Vision and Metabolism attributes between the two agents with the most sugar
Geographic sugar distribution	Provided as a text file that is read into the simulation. Shows the maximum and starting amount of sugar on each grid of the spatial map
Grow back rate (Sugar)	The amount of sugar that grows back, up to the maximum allowed, on each grid, each tick
Initial population	The starting number of agents for each breed
Initial sugar per agent	The amount of sugar each agent starts with selected from a uniform distribution
Learning rate (Lambda)	The smaller the number, the slower the learning rate
Metabolism	The amount of sugar each agent consumes each time period
Q-learning	A rule that permits off-policy learning
Reward	In reinforcement learning, what an agent receives for taking an action while in some state
Rule M	Move to the nearest unoccupied location with the most sugar
Rule R	Provides a replacement agent for each breed when an agent has died
SARSA learning	A rule that permits on-policy learning
Ticks	Discrete temporal intervals of equal value that increase monotonically during model execution. Each Tick has no equivalency to wall clock time
Time limit	The number of ticks at which the simulation will halt
Vision	The distance, in grids, an agent can see
Vision neighborhood	von Neumann - Can see along the four cardinal directions

world randomly while updating their experience. As they age, they increasingly use their experience to make decisions until doing so 95% of the time for the remainder of their life as shown in Fig. 2. In a sense, as the agents get older, they explore less and follow their tacit knowledge more. The difference between these two agent types is how they update their experience. Q-Learning agents make off-policy updates that allow them to follow their existing policy in their Q-Value matrix, and then update their experience by looking outside the policy, focusing on the best available reward. The SARSA agents make on-policy updates following

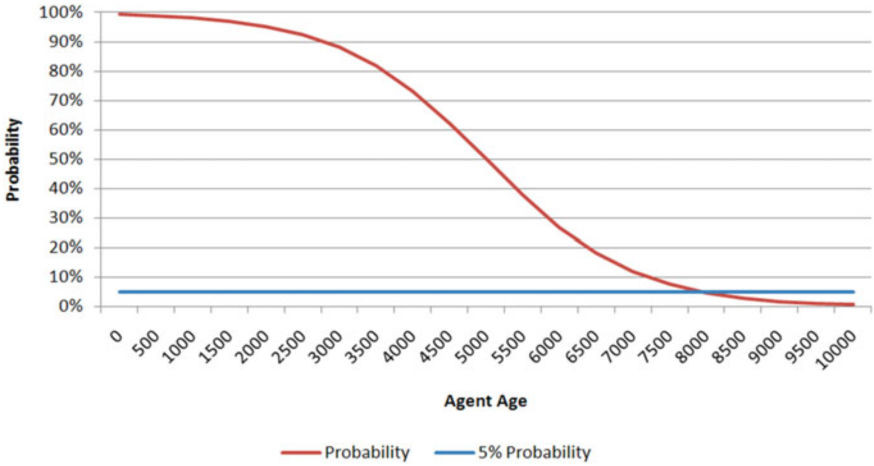

Fig. 2 Age based exploration probability for reinforcement learning agents. The exploration probability ranges from 100% to an artificial lower bound of 5% chosen to ensure agents continue to explore during their entire life

and updating their experience using their existing policy. For a full description, see Sutton and Barto (2018).

4 Results

Before presenting the results for the model, we need to mention our efforts for verification. Here we refer to verification as the process of checking that the model matches its design. This included code walkthroughs and parameter sensitivity testing. These tests ensured that we made no logical errors in the translation of the model into code, and that there were no programming errors. For example, during testing we noticed that the original model used a non-symmetric sugar topology that created noticeable differences in some outcomes when testing the model, specifically when changing the rule sets between two groups. To reduce this bias, a modified sugar topology was created which was symmetrical across the major axis running from the top left to bottom right. In addition, the torus feature was removed eliminating the ability of the agents to move off the edge of the map and appear on the opposing side. This modified sugar topology accompanies the model and is available at https://tinyurl.com/ML-Agents.

Now turning to ascertainment of how the different four rule methodologies (i.e., Rule M, Evolutionary Computing, Q-Learning, and SARSA) interplay with each other, Table 5 shows the initial settings used for testing while Figs. 3, 4, 5, 6, 7, 8 and 9 show pairwise comparisons. Readers should note that the Y-axes for each data graphic in the figures use a base 10 log scale while the X-axes represents 20,001 time intervals (0–20,000 ticks) and the results presented are the mean of 50 model runs.

Table 5 Initial settings for all model runs

Attribute	Initial value	Remark
Corner Start	On	Breeds will start in bottom left and top right corners
Combat	On	Agents will attack
Initial population	400	Maximum agents for corner start
Replace dead	On	Generate replacements for dead agents. If Rule EC is used, replacements will have their Vision and Metabolism created from top two, high sugar agents for their breed
Sugar growback rate	1.0	Note: A setting of 0.6 or less "stresses" the agents with low resources and encourages them to leave their corners

As can be seen in Figs. 3, 4, 5, 6, 7, 8 and 9 there is a general similarity across the main diagonal of each of the data graphics (i.e., when comparing the same rule methods) and this is to be expected, as there is no difference between the two competing groups other than their name (i.e., A and B). However, EC versus EC was the one exception with Group A (Blue) always having the same or slightly better outcomes than Group B (Red). We investigated this and we found it was not due to activation order or incorrect code. Within Sugarscape, there are two main functions of the agents within the model. The first is to collect sugar and this is reflected in the mean wealth that is shown in Fig. 3. Agents utilizing Rule M, the original methodology, always accumulate more sugar against one of the three learning methodologies. Rule M also maintained a higher vision distance (as shown in Fig. 4) and a slightly higher metabolism (Fig. 5). EC learning maintained a significant advantage in wealth (sugar) accumulation over the two RL methods (Fig. 3) and does so with a near equal metabolism (Fig. 5). It does this with a much higher vision distance that declines over time (Fig. 4). A longer run time might have ultimately eliminated this advantage, as the end state is only known to 20,001 ticks. Pitting the two RL methods against each other shows a small advantage of Q-Learning's ability to go outside its own policy (i.e., off policy) as the two groups shifted from exploration to policy as can be seen in Fig. 3. Both maintained almost identical high vision distances (Fig. 4) and low metabolisms (Fig. 5). Compared to the other methods, the agents utilizing the SARSA method do not accumulate so much wealth (Fig. 3).

The second main function of this Sugarscape model is conflict in the form of combat and here there are no clear winners. The EC method accumulated fewer combat deaths when opposing the two RL methods yet had almost equal combat deaths when opposing the Rule M group (Fig. 6). This is possibly attributable to the EC group maintaining a higher vision distance (Fig. 4) against the RL group, enabling better retreat and attack decisions. Rule M, however, was able to maintain a very high vision distance relative to EC (Fig. 4). The two RL methodologies fighting against each other showed a noticeable initial period with very few combat deaths (Fig. 6).

It should also be noted that in the current version of the model, death causes all sugar and combat experience to be lost by the dying agent. The EC method was

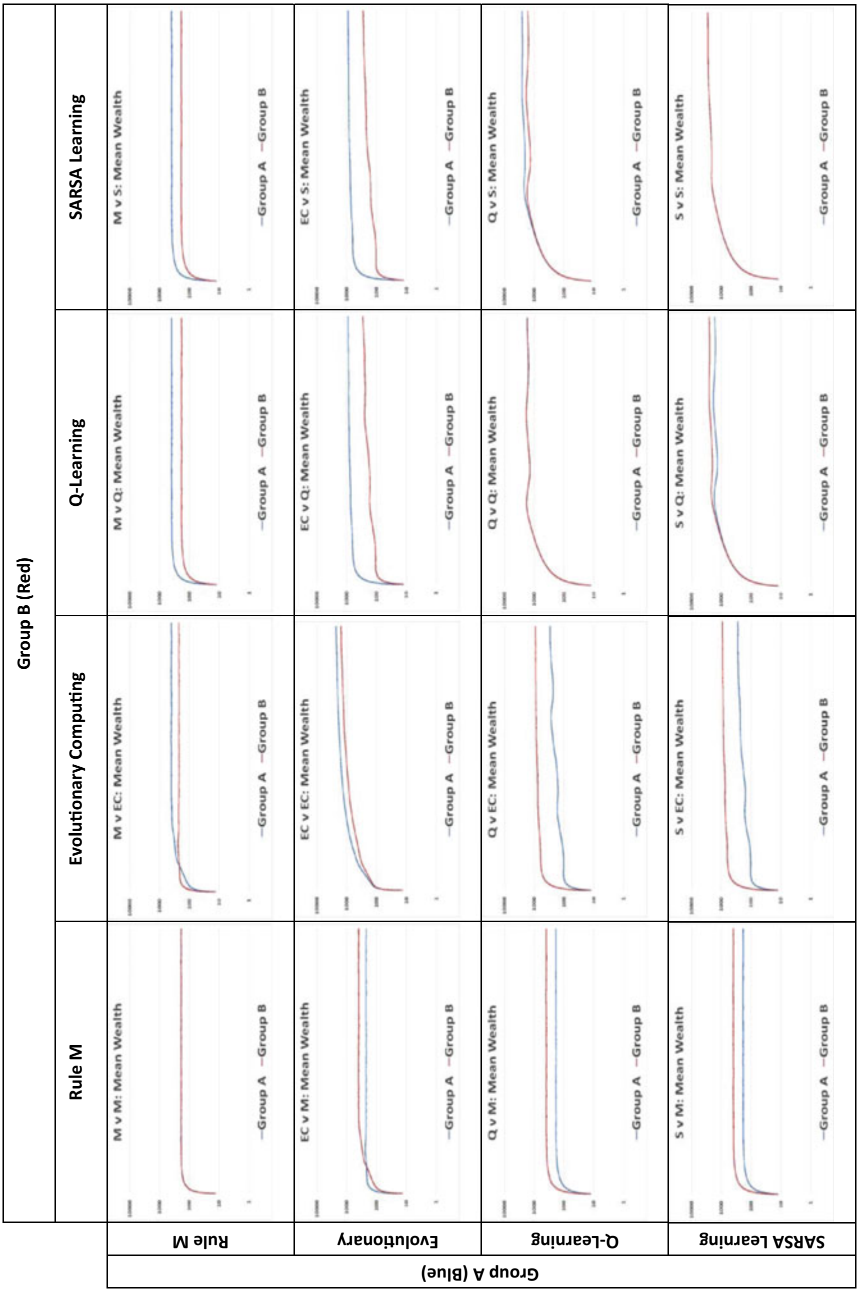

Fig. 3 Mean result for wealth for all rule combinations (50 model runs)

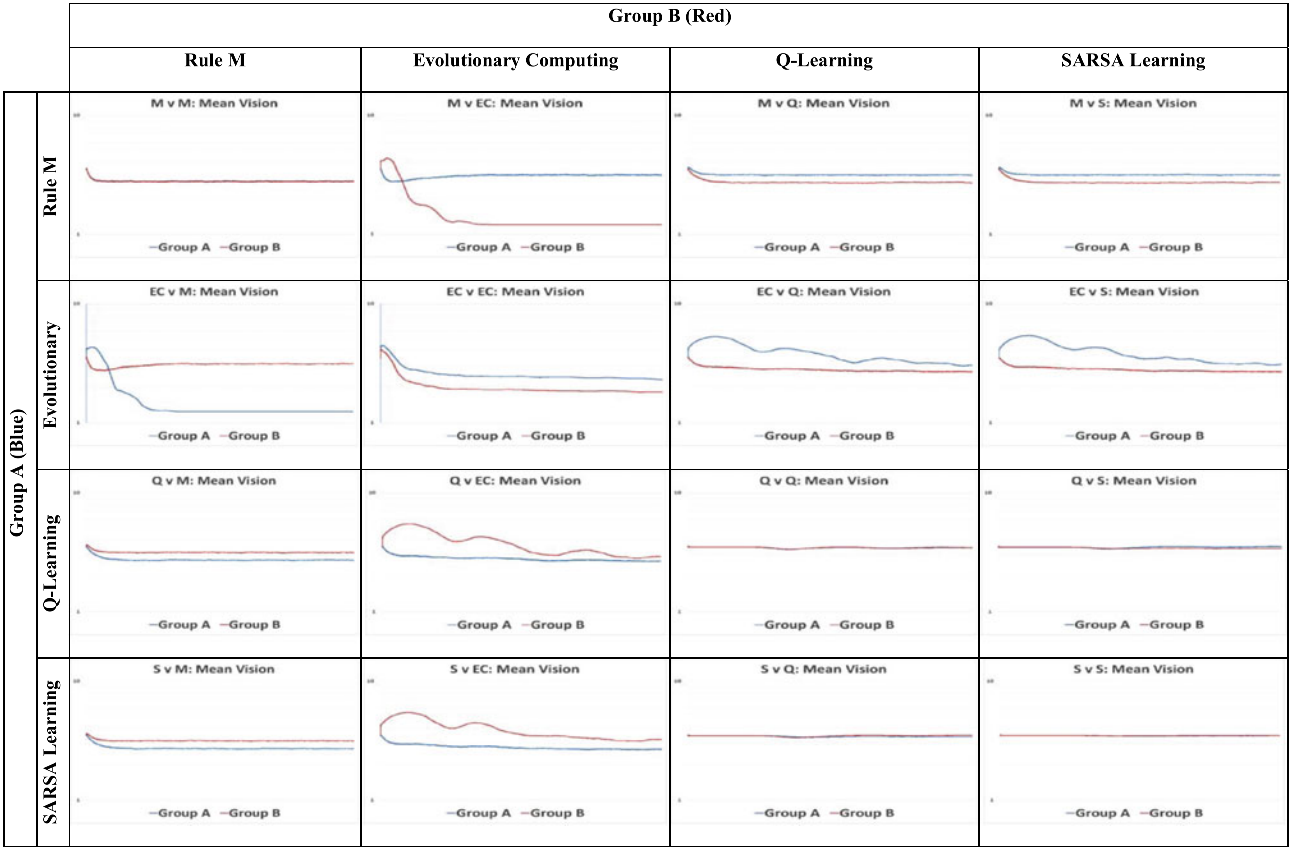

Fig. 4 Mean result for vision for all rule combinations (50 model runs)

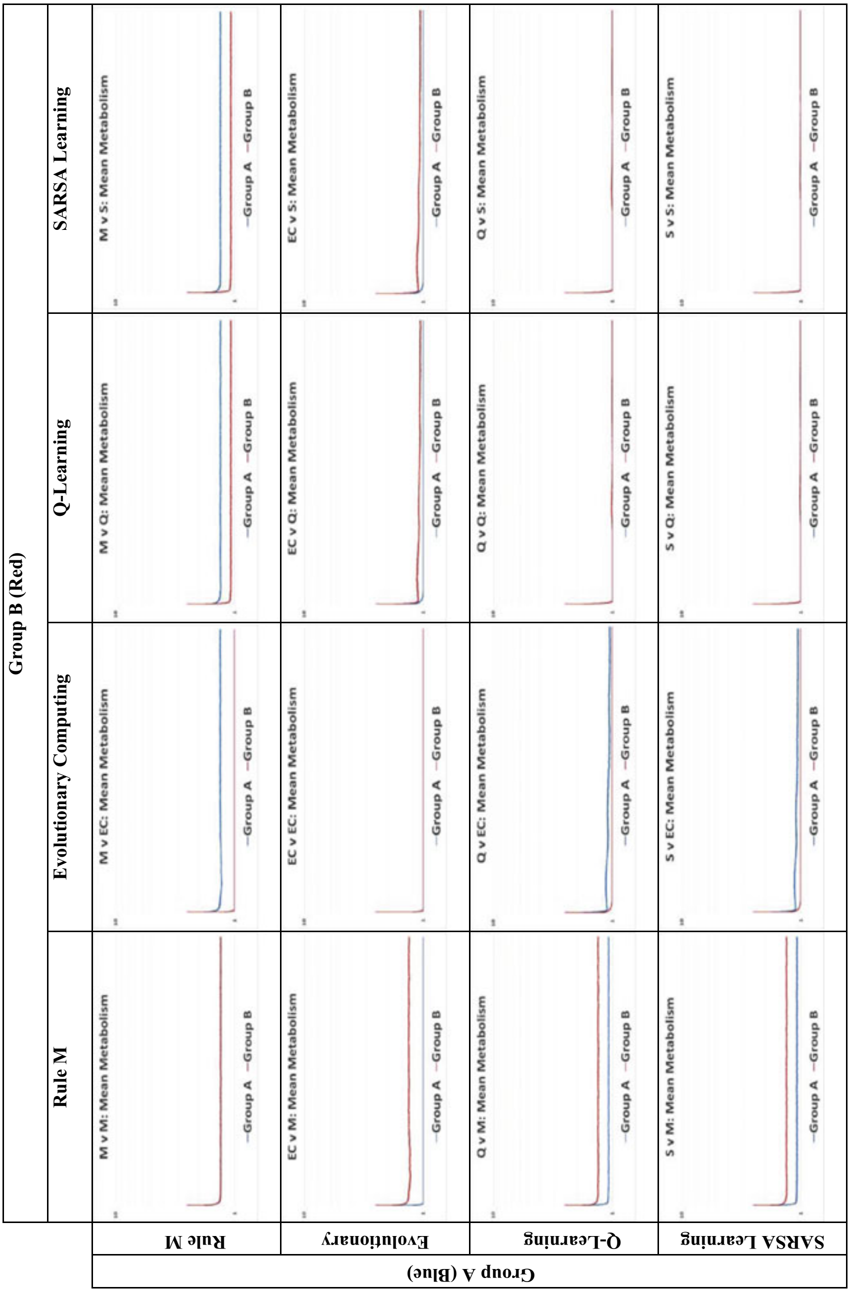

Fig. 5 Mean result for metabolism for all rule combinations (50 model runs)

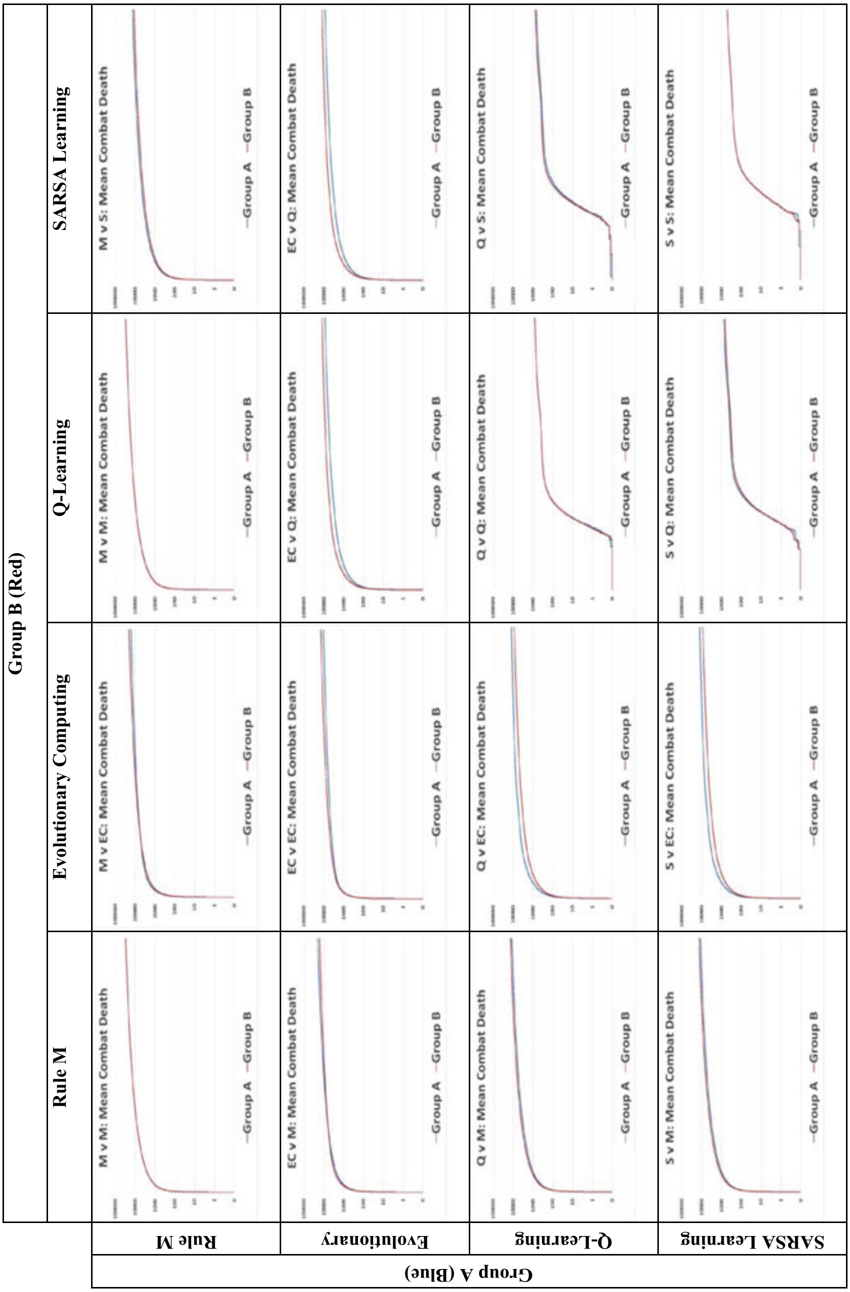

Fig. 6 Mean result for cumulative combat deaths for all rule combinations (50 model runs)

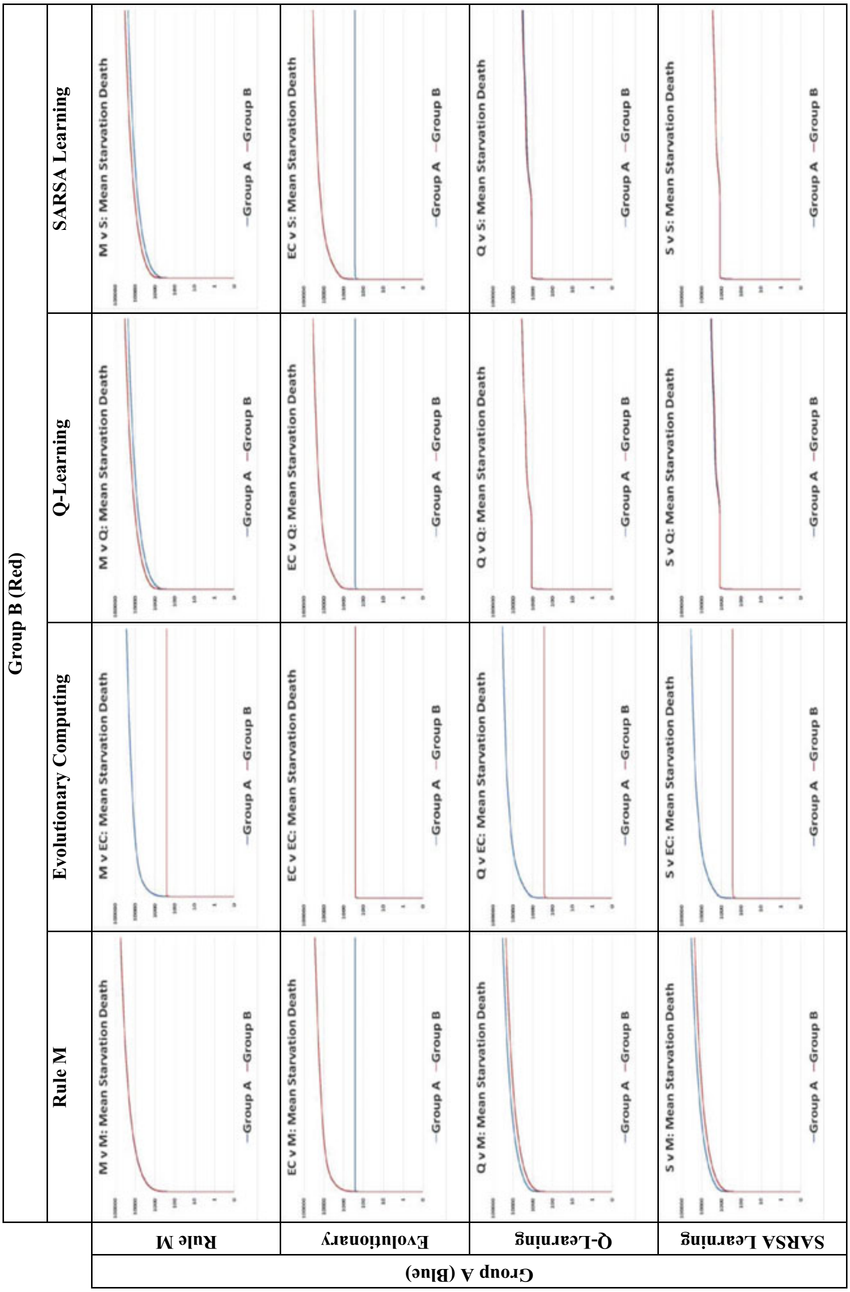

Fig. 7 Mean result for cumulative starvation deaths for all rule combinations (50 model runs)

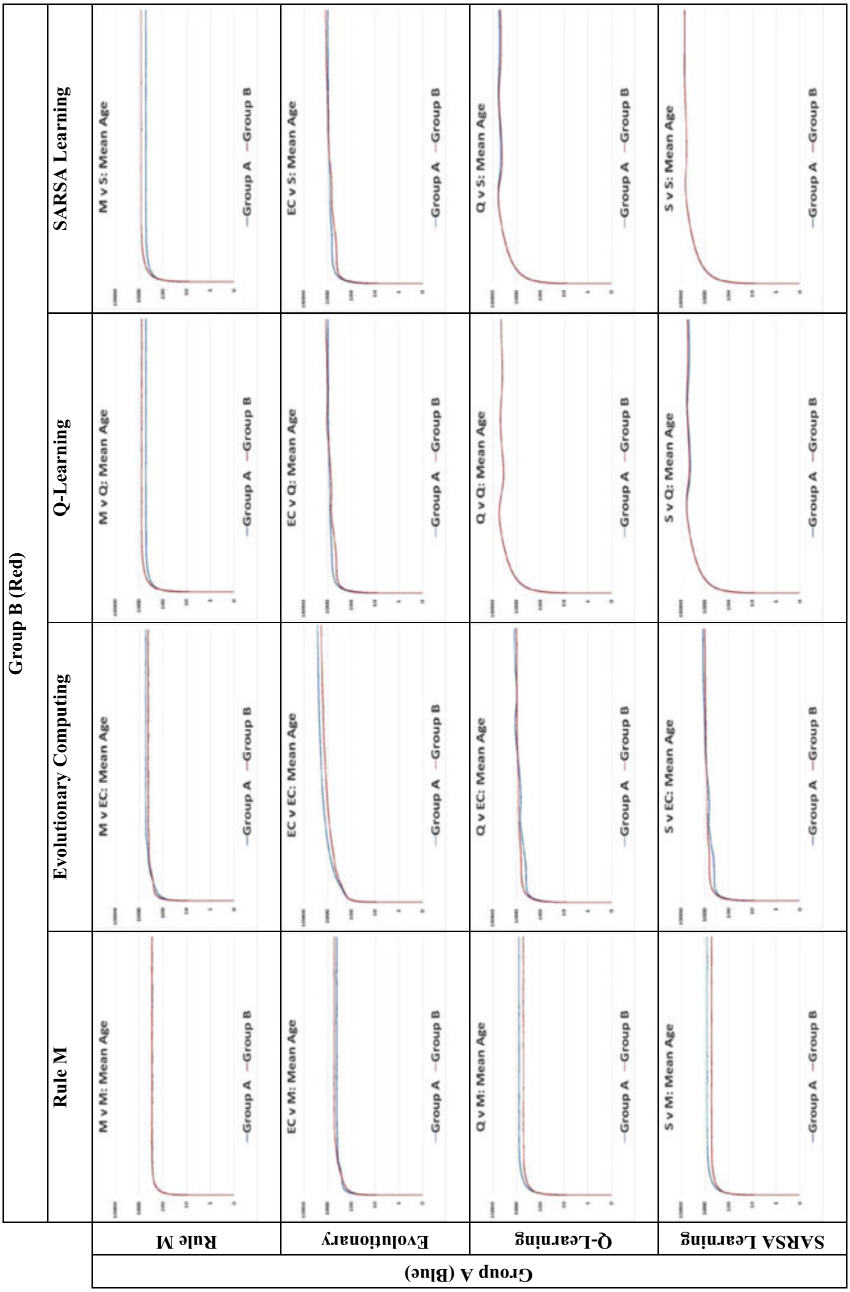

Fig. 8 Mean result for age for all rule combinations (50 model runs)

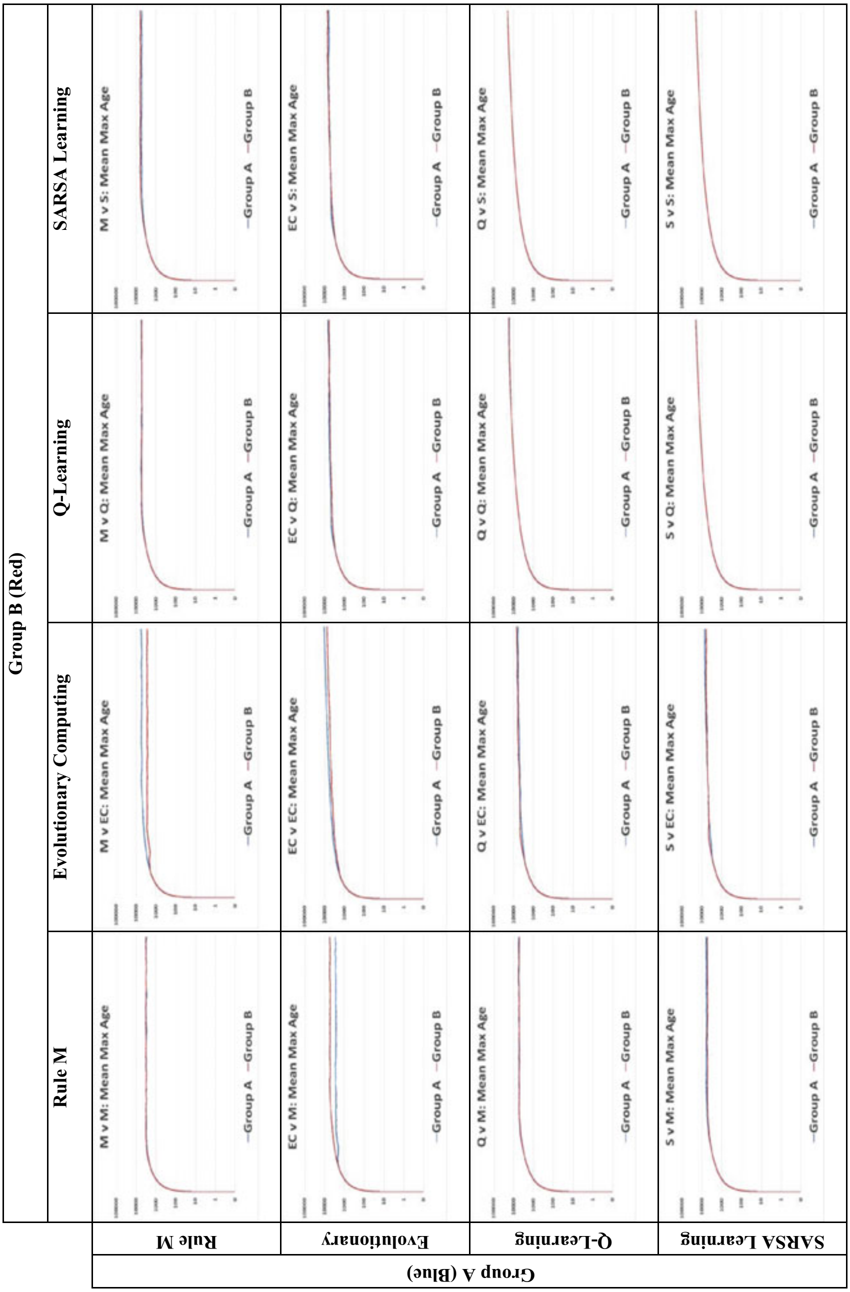

Fig. 9 Mean result for maximum age for all rule combinations (50 model runs)

noticeably superior to the other three methodologies in finding sufficient sugar to metabolize and not starve (Fig. 7). In addition, mean age (Fig. 8) and mean maximum age (Fig. 9) are indicators of experience and sugar gathering opportunities. As RL agents age their individual Q-Value tables reflect their accumulated combat experience and EC agents holding the most sugar become replacement agent templates. All methodologies demonstrated a decrease in mean metabolism (Fig. 5), a positive outcome given a high value could lead to an agent starving to death. Agents utilizing the EC method routinely saw their mean vision decrease over time (Fig. 4). This was an unexpected evolution as superior vision can lead to better sugar mining, defensive actions (retreat in the face of superior numbers), and offensive actions (attacks against an outnumbered opponent). It is possible that combat deaths left mostly low sugar holders and they were low because they lacked vision, however, further analysis is needed to explain this phenomenon. While not reported in the figures, we would like to note that different ML methodologies resulted in variations in model run times. This difference was expected as ML methods can be computationally intensive. For example, using Rule M versus Rule M simulation as a baseline, the SARSA versus SARSA simulation could take as much as seven times as long to complete a single run.

5 Summary

Both agent-based modeling and ML have seen growth over the last two decades, along with the integration of ML within agent-based models (as discussed in Sect. 2). Seldom have agent-based modelers applied different ML methods to the same model and then reported how simulation outcomes differ. This paper does just that. By adapting the Sugarscape model with three types of learning agents (i.e., EC, Q-Learning and SARSA) and contrasting them with Rule M from the original model we found that different learning methods do have an impact on the simulation outcome (as discussed in Sect. 4). While our aim was not to prove which learning method was superior, but rather to provide a way to compare and contrast them, it was surprising that Rule M agents were able to accumulate more wealth than the ML agents. One possible reason for this is that with the ML agents, we did not specifically attempt to tune the simulation. For example, we did not experiment with altering the hyper parameters of the RL models (see Table 3). With that being said, our results do suggest that modelers who wish to use ML methods for agent learning should pay particular attention and justify why they chose one method over another.

The question our results bring up, is it worth the effort to add ML to agent-based models? Creating a model using agents has always required a firm grasp of the simulation's goal, but ML requires additional thought. In traditional rule-based models (e.g., Rule M), the agents' actions are designed specifically to match situations the modeler anticipates. For example, if the agent sees sugar, move to the location with the sugar and consume it. While with ML this is different, taking RL as an example, the modeler needs to consider a range of actions an agent may be tasked to perform and the states they may be in because of these actions (as discussed in Sect. 2). Conversely, the state the agent is in can be used to determine what actions could take place. Rewards can be used to tempt the agent mathematically for each state-action combination. Positive rewards create an inclination to repeat the action, while negative rewards should be like touching a hot stove for the first time. Taking the Sugarscape model presented in this paper, combat was an important part of this demonstration and agents are dependent on the presence of their enemy (i.e., the other group) for learning. RL agents that do not encounter the enemy, never learn to attack or retreat. EC agents evolve based on representative agents with the most accumulated sugar. High sugar EC agents that are killed by the enemy cannot pass their attributes onto new agents. For both types of learning agents, enemy actions have consequences beyond a single combat action. However, going back to the question posed at the beginning of this paragraph, we would argue that the answer is yes, it is worth adding ML to agent-based models, if the goal is unachievable by simpler methods or if you want the agents to learn from good and bad experiences. Another consideration when it comes to using ML is the increase in computational resources needed for them. Today's era of big data and cloud-based computing has increased the availability of such resources, but the cost is still a limitation and wasted time cannot be recovered. For example, our RL agents needed time to explore actions before beginning to exploit them and SASRA took seven times longer (wall clock time) to execute than Rule M over the same number of time steps (ticks).

While the methods used within this paper are well established within the ML field, it paves the way to exploring newer ML methodologies in the social science community. Looking ahead, using deep RL and combining ML methodologies in the same agent is worthy of future research. It is not surprising that others (Sutton and Barto 2018) have combined RL and an artificial neural network (ANN). The ANN can act as a function to reduce a large number of inputs to a smaller set that focuses on critical features. In a different approach, EC could be used as a means for two successful RL agents to pass their knowledge to a new agent. Another area of further work would be to explore other well know agent-based models and explore the impact that ML would have on their end states. With all this being said, our paper's contribution to the field of agent-based modeling is not only to show how previous researchers have used ML but also to directly compare and contrast how different ML methods used in the same model impact the simulation outcome which is rarely discussed, thus helps bring awareness to researchers who are considering using intelligent agents to improve their models.

Appendix A: Examples of Utilizing Evolutionary Computing Within Agent-Based Models to Study Social Issues

In this appendix, readers will find a selection of papers that have utilized EC within agent-based models to study social issues. Before presenting Table A.1, we provide a brief explanation of column headings to aid the reader:

- **Author**: The author(s) and year of publication.
- **Application**: All papers fall under the category of Sociology. The sub-category within sociology is listed.
- **Focus**: The author's intent in writing the paper leans either toward solving or exploring some sociology issue or toward demonstrating how an EC methodology could be applied.
- **Entity**: The entity types the agents represent in the model.
- **Behavior**: The method used by each agent to model human behavior. This is an extension of Kennedy's (2012) typology of mathematical behavior of human agents. All behaviors are mathematical and a type of Machine Learning (ML). The types can be evolutionary computing/evolutionary algorithm (EC/EA), evolutionary computing/evolutionary programming (EC/EP), artificial neural network (ANN), or reinforcement learning (RL).
- **Agent Scale**: The number of agents used in the model shown in a power of ten notations.
- Spatial Scale: The spatial size used by the model, if any. Network is a special spatial scale where there is no distance, but there is adjacency.
- **Time Scale**: Shown as interval or ordinal from Steven's (1946) typology. Interval means the temporal distance between units is identical. The unit can be explicit (years) or abstract (steps). Ordinal means the distance between units is undefined but is monotonic and usually increasing (generation).

Appendix B: Examples of Utilizing Reinforcement Learning Within Agent-Based Models to Study Social Issues

In this appendix, readers will find a selection of papers that have utilized RL within agent-based models to study social issues. To assist with interpretation of Table B.1, the column headings are the same as in Table A.1 with the exception of behavior. Here behavior refers to the method used by each agent to model human behavior. This is an extension of Kennedy's (2012) typology of mathematical behavior of human agents. All behaviors are mathematical and a type of Machine Learning (ML). The types can one of the following *Q-Learning* (QL), *Temporal-Difference* (TD), *Bush-Mostellar* (BM), *State* → *Action* → *Reward* → *State* → *Action* (SARSA), and *Learning Automata* (LA).

Table A.1 A selection of applications utilizing evolutionary computing to study social science applications

Author	Application	Focus[a]	Entity	Behavior	Agent scale	Spatial scale	Time scale
Arifovic (1994)	Economics	S	Firm	ML/EC/EA	10^0	None	Interval, Steps (10,000)
Chen and Yeh (1996)	Economics	M	Firm	ML/EC/EP	10^2	None	Interval, Steps, Generations (1,000)
Curran and O'Riordan (2007)	Social Dynamics	S	Individual	ML/EC/EA ML/ANN	10^1	Network	Interval, Steps (400)
Dionne et al. (2019)	Social Dynamics	S	Individual	ML/EC/EA	10^2	Network	Interval, Steps (60)
Edmonds (1999)	Social Dynamics	S	Individual	ML/EC/EP	10^0	None	Interval, Weeks (100)
Fischer (2003)	Social Dynamics	M	Individual	ML/EC/EA	10^0	None	Interval, Steps (10,000)
Francisco and Jorge dos Reis, (2008)	Teamwork	M	Individual	ML/EC/EP	10^2	Interval, Grid (5,000 × 5,000)	Ordinal (100)
Grefenstette (1992)	Teamwork	M	Individual	ML/EC/EP	10^0	None	Interval, Steps, Generations (100)
Haynes (1996)	Teamwork	M	Individual	ML/EC/EP	10^0	Interval, Grid (30 × 30)	Interval, Steps (100)
Hsu and Gustafson (2002)	Teamwork	M	Individual	ML/EC/EP	10^3	Interval, Grid (20 × 20)	Interval, Steps (400)
Jang et al. (2019)	Social Dynamics	S	Individual, Organization	ML/EC/EA	10^2	Network	Interval
Jim and Giles (2000)	Teamwork	M	Individual	ML/EC/EA	10^2	Interval, Grid (30 × 30)	Interval, Steps (5,000)
Klüver & Stoica (2003)	Social Dynamics	M	Individual	ML/EC/EA ML/ANN	10^0	Network	Interval
Kunz (2011)	Social Dynamics	S	Group	ML/EC/EA	10^1	None	Interval, Steps (200)

(continued)

Table A.1 (continued)

Author	Application	Focus[a]	Entity	Behavior	Agent scale	Spatial scale	Time scale
Manson (2005)	Economics	S	Household, Organization	ML/EC/EP	10^1	Interval, Grid (cell 28.5^2 m)	Interval, Years (9)
Tanev and Shimohara (2003)	Teamwork	M	Individual	ML/EC/EP	10^0	Interval, Grid [mm] (1,600 × 1,000)	Interval, Half-Second (600)
Vila (2008)	Economics	S & M	Individual	ML/EC/EA	10^3	None	Interval, Steps (500)
Xianyu (2010)	Social Dynamics	S	Individual	ML/EC/EA ML/RL	10^3	Network	Interval, Steps (5,000)
Yamamoto et al. (2019)	Social Dynamics	S	Individual	ML/EC/EA	10^2	None	Interval, Steps [200 Rounds × 200 Generations] (40,000)

[a]M is for Methodology and S is for Solve

Table B.1 A selection of applications utilizing reinforcement learning to study social science applications

Author	Application	Focus[a]	Entity	Behavior	Agent scale	Spatial scale	Time scale
Chmura and Pitz (2007)	Social Dynamics	S	Individual	ML/RL/QL	10^1	None	Interval, Steps (500)
Christensen and Sasaki (2008)	Social Dynamics	S	Individual	ML/RL/TD	10^1	Square Meters (4,000)	Interval, 25 ms (4,880)
Claus and Boutilier (1998)	Social Dynamics	M	Individual	ML/RL/QL	10^0	None	Interval, Steps (2,500)
Clempner (2017)	Social Dynamics	M	Individual	ML/RL/TD	10^0	None	Interval, Steps (Unknown)
Hao and Leung (2013)	Social Dynamics	S	Individual	ML/RL/QL	10^2	None	Interval, Rounds (5,000)
Izquierdo et al. (2008)	Social Dynamics	M	Individual	ML/RL/BM	10^0	None	Interval, Steps (1,000,000)
Junges and Klügl (2011)	Social Dynamics	M	Individual	ML/RL/QL	10^0	Continuous, Meters (20 × 30)	Interval, Half-Second (50,000)
Macy and Flache (2002)	Social Dynamics	M	Individual	ML/RL/BM	10^0	None	Interval, Steps (500)
Mahadevan and Connell (1992)	Task Managing	M	Individual	ML/RL/QL	10^0	Interval, Grid (37 × 19)	Interval, Steps (2,000)
Nowé et al. (2006)	Social Dynamics	M	Individual	ML/RL/LA	10^0	None	Interval, Steps (500)
Ramchandani et al. (2017)	Economics	M	Individual	ML/RL/QL	10^3	None	Interval, Months (540)
Sallans et al. (2003)	Economics	S	Firms, Traders, & Consumers	ML/RL/ SARSA	Not Known	None	Interval, Steps (4,500)

(continued)

Table B.1 (continued)

Author	Application	Focus[a]	Entity	Behavior	Agent scale	Spatial scale	Time scale
Takadama et al. (2008)	Social Dynamics	M	Individual	ML/RL/QL	10^0	None	Interval, Steps (10,000,000)
Tan (1993)	Teamwork	M	Individual	ML/RL/QL	10^0	Interval, Grid (10 × 10)	Interval, Steps (10,000)
Tanabe and Masuda (2012)	Social Dynamics	M	Individual	ML/RL/BM	10^3	None	Interval, Steps (200)
Wall (2018)	Social Dynamics	S	Organization Unit	ML/RL/BM	10^0	Network	Interval, Steps (Unknown)
Wolpert et al. (1999)	Social Dynamics	M	Individual	ML/RL/QL	10^2	Network	Interval, Weeks (4,000)
Zschache (2017)	Social Dynamics	M	Individual	ML/RL/QL	10^4	Network	Interval, Steps (1,000)

[a]M is for Methodology and S is for Solve

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