Endüstri Mühendisliği / Journal of Industrial Engineering 34(0), 91-109, 2023
(41. Yöneylem Araştırması ve Endüstri Mühendisliği (YA/EM 2022) Ulusal Kongresi Özel Sayısı)

Endüstri Mühendisliği / Journal of Industrial Engineering

https://dergipark.org.tr/tr/pub/endustrimuhendisligi

THE EL FAROL BAR PROBLEM: A COMPARATIVE ANALYSIS OF EXPECTATION MODELS USED IN DECISION MAKING

Burak ÇETİNER[1*], Hakan YASARCAN[2]

[1]Marmara University, Faculty of Engineering, Industrial Engineering Department, ISTANBUL, ORCID No : http://orcid.org/0000-0002-4548-5000
[2]Boğaziçi University, Faculty of Engineering, Industrial Engineering Department , ISTANBUL, ORCID No : http://orcid.org/0000-0002-8767-458X

Keywords

Adaptive learning
Agent-based modelling
Bounded rationality
Decision-making
El Farol Bar Problem

Abstract

Arthur (1994) introduces the El Farol Bar Problem (EFBP) in his article "Bounded Rationality and Inductive Reasoning". He creates an agent-based model of the EFBP and uses it to explain the importance of the concept of "bounded rationality". According to Arthur, deductive reasoning will not create decisions that will produce a desired behavior for the EFBP. Hence, boundedly rational agents using inductive reasoning in decision-making is a must for this and similar types of problems. Arthur uses the EFBP to introduce the fundamentals of the complexity economics and criticizes the assumptions of conventional economic theories. We extend Arthur's work by creating different types of agents and comparing them in terms of performance measures such as mean attendance and standard deviation of attendance. We introduce adaptive learning agents that use inductive reasoning in forming their decisions expecting an improvement in the overall performance of the agents. Throughout the analysis of the EFBP, we discover the role of heterogeneity and the detrimental effect of using the weekly attendance information. Unexpectedly, as a result of our findings, the

*Sorumlu yazar; e-posta : burak.cetiner@marmara.edu.tr

doi : https://doi.org/10.46465/endustrimuhendisligi.1264061

behavior of adaptive learning agents converges to the behavior that would be expected from agents using deductive reasoning.

EL FAROL BAR PROBLEMİ: KARAR VERMEDE KULLANILAN FARKLI BEKLENTİ MODELLERİNİN KARŞILAŞTIRILMALI ANALİZİ

Anahtar Kelimeler

Ajan temelli benzetim
El Farol Bar Problemi
Karar verme
Sınırlı rasyonellik
Uyarlanabilir öğrenme

Öz

Arthur (1994) "Bounded Rationality and Inductive Reasoning" adlı makalesinde El Farol Bar Problemini (EFBP) tanıtmaktadır. EFBP'nin etmen tabanlı bir modelini oluşturmakta ve bunu "sınırlı rasyonellik" kavramının önemini açıklamak için kullanmaktadır. Arthur'a göre, tümdengelimli akıl yürütme, EFBP için istenen bir davranışı üretecek kararlar oluşturamayacaktır. Bu nedenle, karar vermede tümevarımsal akıl yürütmeyi kullanan sınırlı rasyonel ajanlar, bu ve benzeri türdeki problemler için bir zorunluluktur. Bu çalışmada, Arthur'un çalışmasını farklı beklenti modelleri kullanan ajanlar oluşturarak genişletiyoruz ve onları ortalama katılım ve standart sapma gibi performans ölçütleri açısından karşılaştırıyoruz. Ajanların genel performansında bir gelişme bekleyerek katılım kararlarını oluştururken tümevarımsal muhakemeyi kullanan adaptif öğrenme yöntemini kullanıyoruz. EFBP analizi boyunca, haftalık katılım bilgisini kullanmanın olumsuz etkisini ve heterojenliğin rolünü keşfediyoruz. Bulgularımıza göre, beklemediğimiz şekilde adaptif öğrenen ajanların davranışı, tümdengelimli muhakeme kullanan ajanlardan beklenebilecek davranışa yakınsıyor.

Araştırma Makalesi		Research Article	
Başvuru Tarihi	: 30.01.2023	Submission Date	: 30.01.2023
Kabul Tarihi	: 29.07.2023	Accepted Date	: 29.07.2023

1. Introduction

W. B. Arthur (1994) introduces the El Farol Bar Problem (EFBP) in his article "Bounded Rationality and Inductive Reasoning". The EFBP has an agent-based structure in which independent agents make decisions according to their expectation models. He discusses that the EFBP forces agents to use inductive reasoning. If deductive reasoning were valid for agents in the EFBP, they would all use the same exact expectation model; either all will attend to the bar at the same time, or, simultaneously, all will choose not to attend. Accordingly, agents will be forced to differ in their own expectation models breaking up the “commonality of expectations”. As a “deductively rational solution” to the problem is impossible, they must use different expectation models. Therefore, the agents in the EFBP can only be defined as “boundedly rational” (Arthur, 1994). Arthur uses the EFBP to introduce the fundamentals of the complexity economics and criticizes the assumptions of conventional economic theories.

The EFBP contributes to the literature on bounded rationality. The term “bounded rationality” can be defined as the rational choice of a decision-maker within the limitations of both knowledge and computational capacity (Simon, 1990). The EFBP is inspired by a real bar located in Santa Fe, New Mexico, and Arthur uses the problem to show that perfect information is not available for decision-makers in such a decision environment. When the information is limited due to the nature of the problem, decision-makers should use inductive reasoning to make decisions. After introducing these ideas, Arthur criticizes the assumptions of conventional economic theory. He claims that conventional economics is based on perfectly rational agents and static equilibriums that are analytically obtained (Arthur, 1994). However, according to Arthur’s opinion, the economy should be analyzed as “an evolving system rather than a deterministic and mechanistic nature” (Arthur, 1999). He uses the agent-based model to show the importance of bounded rationality and inductive reasoning aiming to introduce a new field, “complexity economics”.

We categorize the studies on the EFBP into five main areas: the studies that focus on complexity economics (Arthur, 1994 and 1999; Foxon, Köhler, Michie and Oughton, 2013; Elsner, 2017; Manson, 2001), the payoff/utility of the agents (Challet and Zhang, 1997; De Cara, Pia and Guinea, 2008; Sellers, Sayama and Pape, 2020; St Luce and Sayama, 2020), the EFBP applications (Adler and Blue, 2002; Chen and Gostoli, 2017; Edmonds, 1998; Hausken, Banuri, Gupta, and Abbink, 2015), minority game and its extensions (Chakrabarti, 2007; Challet and Zhang, 1997; Galib and Moser, 2011; Galstyan, Kolar, and Lerman., 2003; Lustosa and Cajuearia, 2009), and the modelling of the EFBP (Fogel, Chellapilla and Angeline, 1999; Garofalo, 2006; Ponsiglione, Roma, Zampella and Zollo, 2015; Rand and Stonedahl, 2007; Wilensky and Rand, 2015). The work presented in this paper can be considered under the modelling of the EFBP literature.

There are different experiments and various models on the EFBP in the literature. Garofalo (2006) explains how he implemented the EFBP on the NetLogo environment in his article. He discusses the assumptions of Arthur, the predictors working mechanism, and parameters of the model. Fogel et al. (1999) take Arthur's challenge that is to enrich the predictors with genetic algorithms instead of using a “bag of strategies", so that the agents will use “more intelligent" predictors. Their findings inspire Rand and Stonedahl (2007) to study the relationship between the “computational power" and attendance at the bar in the EFBP. They use the NetLogo model (Wilensky and Rand, 2015) with the formulation of Fogel et al. (1999) for different levels of computational power and their results support Fogel et al. (1999)'s findings. Lastly, Ponsiglione et al. (2015) conduct simulation experiments about efficiency and fairness in the EFBP using four different models.

Arthur assumes there is a population of 100 people who decide whether to go to the bar or not each week. The bar has a certain capacity, and the bar capacity is taken as the 60% of the whole population, namely, 60 people. For an individual agent, the night at the bar is enjoyable only if the bar is not overcrowded. Therefore, the correct decision for an individual agent would be to attend the bar if there would be in total 60 or fewer people at the bar for a given week. Similarly, the correct decision would be to stay home if there would be more than 60 people attending the bar. Accordingly, agents decide whether to go to the bar or to stay home according to their expected number of people who will attend the bar that week. If the expectation of an agent is less than 60 people, the agent decides to go to the bar, otherwise (i.e., if the expectation is greater than or equal to 60 people) the agent stays at home. This decision-making rule has an implication at the population level; as the attendance diverges away from the bar capacity, the total number of correct decisions decreases. The highest number of correct decisions occurs when the attendance value is equal to the capacity of the bar.

There is no communication between agents and the experience they had in the previous weeks does not affect the decisions of the agents. Nevertheless, Arthur (1994) states that “the only information available is the numbers who came in past weeks”. In this case, deductive reasoning fails to create a good utilization of the bar. In other words, if the agents use the same information (i.e., attendance values) and the same expectation formulation as deductive reasoning suggests, the expectations of the agents do not differ. Consequently, “if all believe few will go, all will go” and “if all believe most will go, nobody will go” (Arthur, 1994). Consequently, Arthur decides to assign a different set of strategies to each agent randomly. Each strategy corresponds to a predictor. He assumes that each agent has “k” predictors for the weekly expectations and the “active predictor” of the agent determines the weekly expectation value for that agent for the given week. The active predictor is the current most accurate predictor. The accuracy of the predictors is updated every week by comparing the predicted value to the actual attendance value.

In this study, we conduct an analysis on the EFBP by extending Arthur's work creating different types of agents and comparing them in terms of performance measures such as mean attendance and standard deviation of attendance. We introduce adaptive learning agents that use inductive reasoning in forming their decisions expecting an improvement in the overall performance of the agents. The comparative analysis of the expectation models with respect to the performance measures allows us to make inferences about this complex adaptive system. Furthermore, we determine which agent type is more successful with respect to different performance measures and explain the reasons behind this success.

The EFBP can be constructed as an agent-based model and almost all studies in the literature used agent-based modelling as the main methodology. Our primary approach is also agent-based modelling and simulation, which is consistent with the literature In this study, we compare three distinctive agent types that use different expectation models. We create a Python code for the agent-based simulations of the EFBP aiming to compare the resulting aggregate behavior generated by the three different agent types. Agents that use random expectations and agents that use a "bag of strategies" already exist in the literature. In addition, we introduce agents with adaptive learning to the EFBP. These agents use the exponential smoothing method to form expectations. We want to study the performances of these three types of agents and reach a conclusion about the reasons behind a "good performing" expectation model. Sterman (1987) claims that expectations are usually represented as adaptive learning processes in system dynamics models and, usually, adaptive learning is captured by the exponential smoothing method. In other words, exponential smoothing is an inductive method that can represent the behavioral expectations of humans in a dynamic simulation model. Moreover, Arthur (1994) claims that deductive reasoning in decision-making is not valid for the agents in the EFBP and inductive reasoning is a must. Based on these two claims, we hope that agents with adaptive learning will potentially outperform the other two types of agents. Research and publication ethics were followed in this study.

2. Three Different Agent Types

In our model, we use three different expectation models and compare them with respect to the overall performance measures such as mean attendance and standard deviation of attendance. Each expectation model is represented by a different type of agent. The flowcharts for the decision-making process of each agent type are given in Figure 1, Figure 2, and Figure 3. Three agent types that use different expectation models are created: (i) random expectations, (ii) "bag of strategies", and (iii) adaptive learning respectively.

2.1 Type 1 Agents (Random expectation)

Type 1 Agents have individual random expectation models. They simply create their expectations randomly without using any strategy for each week. Our code generates random numbers, and they are assigned to each agent for each week to determine the agents' weekly expectations. These random numbers are assumed to be uniformly distributed between 0 and 99 so that the expected number of people for an agent on the given week can be any integer between 0 and 99. If the expectation of an agent is less than the bar capacity, which is 60 people in this problem, that agent decides to attend the bar. If the expectation of an agent is greater or equal to the bar capacity, that agent does not attend the bar. The flowchart of the algorithm for Type 1 Agents is given in Figure 1.

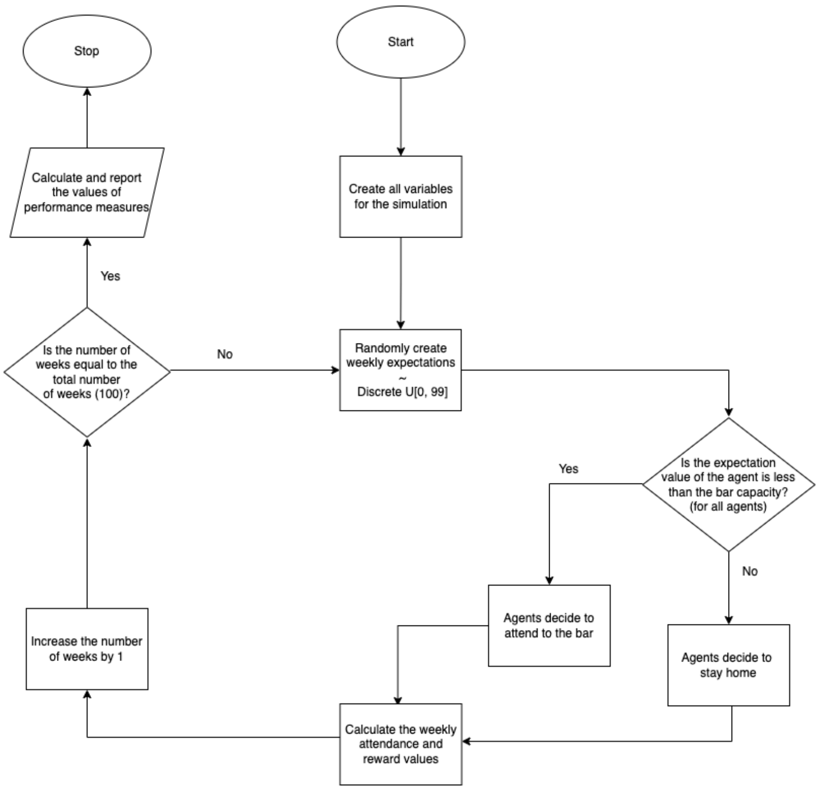

Figure 1. Flowchart of the Algorithm for Type 1 Agents

2.2 Type 2 Agents ("bag of strategies")

We write a code for Arthur/Garofalo's agents aiming to satisfy the descriptions given in Arthur (1994) about the strategies and strategy switching mechanism. We create m strategies where m is 200 as stated by Garofalo (2006). These m strategies create expectation values for each week by using "calculated predictors", in other words, a "bag of strategies". Arthur (1994) gives a few examples of the predictors. These are tit-for-tat, mirror image, moving average, trends, and n-period cycle detectors. As Arthur (1994) does not give the parameters and exact number of strategies assigned to each agent, we use the details given by Garofalo (2006) and Ponsiglione et al. (2015). For Type 2 Agents, we use the following strategies with a maximum memory size of twenty weeks and a total number of 200 strategies: tit-for-tat, the mirror image of tit-for-tat, fixed rules, trends, the mirror image of trends, moving averages, pessimist, and optimist predictors. These 200 strategies consist of the combination of 10 different prediction method. Moreover, if the history of the attendance information is not enough for prediction, the predictor uses random expectation (Garofalo, 2006). For example, a predictor takes the five weeks moving average to predict the expectation for the given week, but if the simulation is on the third week, then the predictor uses random expectation. Arthur does not specify the exact number of the strategies. Therefore, we take Garofalo's assumption as a reference value which is six strategies.

After the strategies are assigned, they are used to create expectations for every simulated week. For a given week, the current "active predictor" of an agent determines the expected attendance value for that agent. The active predictor is updated for every agent at the end of every simulated week by comparing the expected errors of the predictors assigned to each agent. The error of a predictor is calculated based on the difference between the new attendance value and the estimated value generated by that predictor; the difference values are exponentially smoothed (Ponsiglione et al., 2015). The active predictor is the current most accurate one (i.e., the one with the smallest error term) among the assigned strategies. The error term equation for each strategy can be expressed by the following equation:

$$Error_{s,j} = (1 - \lambda) \cdot Error_{s-1,j} + \lambda \cdot \left| Strategy_{s,j} - Attendance_{s} \right| \quad (1)$$

where j is the counter variable for number of strategies

and s is the counter variable for number of weeks.

The decision mechanism of deciding to attend or not to attend the bar remains the same. The flowchart of the algorithm for Type 2 Agents is given in Figure 2.

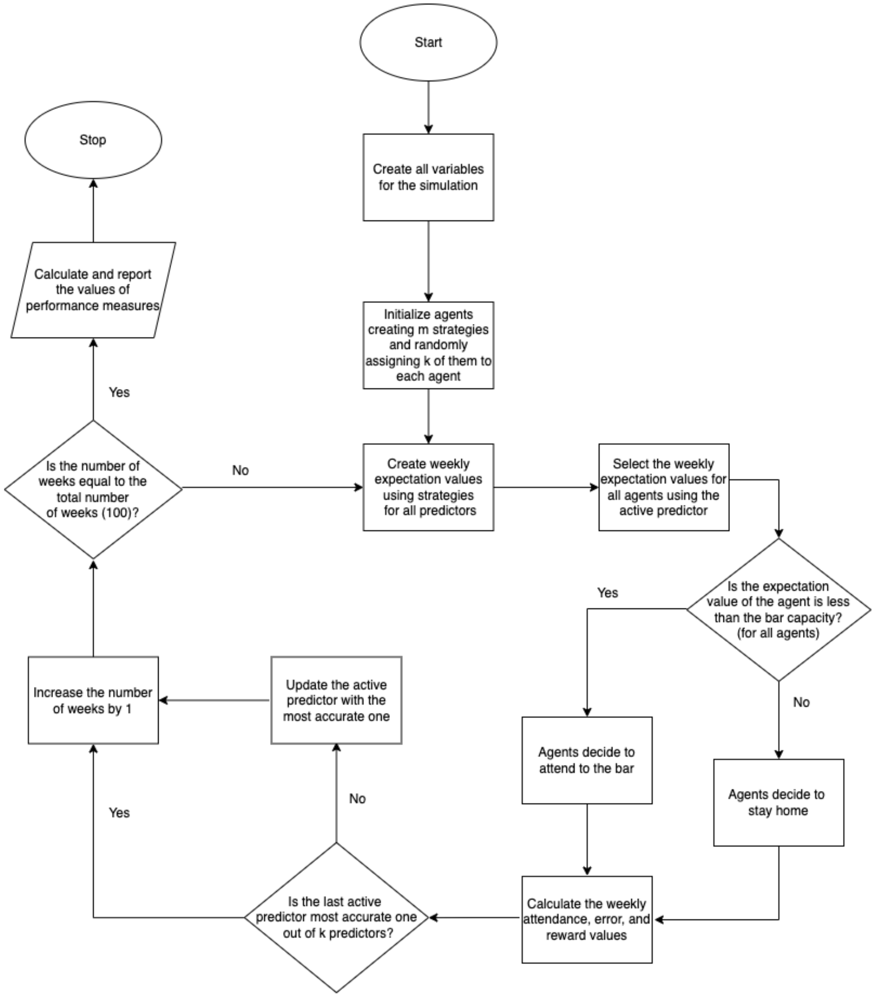

Figure 2. Flowchart of the Algorithm for Type 2 Agents

2.3 Type 3 Agent (Adaptive Learning)

Our third expectation model results in boundedly rational agents with adaptive learning. Various learning mechanisms are used to experiment with the EFBP. However, there are no studies in the EFBP literature using the exponential smoothing method in forming expectations. We name the agents that use exponential smoothing method as Type 3 Agents and this agent type is our contribution to the EFBP literature. Sterman (1987) claims that exponential smoothing is a good way to represent adaptive learning. In other words, he describes an inductive method to reflect behavioral expectations of humans in a dynamic simulation model (Sterman, 1987). In order to create Type 3 Agents, we first create individual smoothing parameter values (α_i) for each agent. The smoothing parameter value indicates the weight of the new information in the exponential smoothing formulation. We use continuous uniform distribution while randomly assigning the smoothing parameter values between 0.1 and 0.3 as suggested in the literature (Gardner Jr, 1985)

An exponential smoothing formula with a relatively high smoothing parameter value will give higher weight to the new attendance information in obtaining expected values compared to a formula that has a lower smoothing parameter value. The initial expected values are created randomly between 0 and 99. The equation for creating expectations with simple exponential smoothing formulation is expressed as

$$\text{Expectation}_{s,j} = (1 - \alpha_i)\cdot\text{Expecation}_{s-1,j} + \alpha_i\cdot\text{Attendance}_{s-1} \quad (2)$$

where j is the counter variable for number of strategies

and s is the counter variable for number of weeks.

Every simulated week, a new attendance value is obtained as a result of the individual decisions of the agents and, using this new attendance value, the expected value for the next week is updated. Individual smoothing parameter values makes each agents' expected values to differ from one to another. On the contrary, if all agents used the same alpha value, they would have the same expectation formulation, which eventually creates a dynamic behavior that would emerge from deductive reasoning as it is shown in Figure 3. Arthur (1994) expresses this case as "if all believe few will go, all will go" and "if all believe most will go, nobody will go". The flowchart of the algorithm for Type 3 Agents is given in Figure 4.

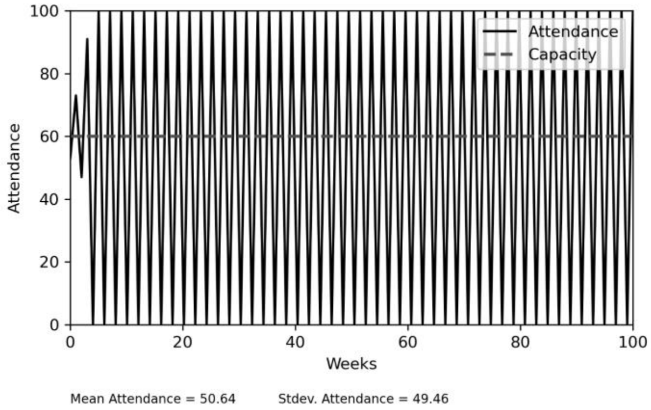

Figure 3. Dynamics With The Same Smoothing Parameter Value

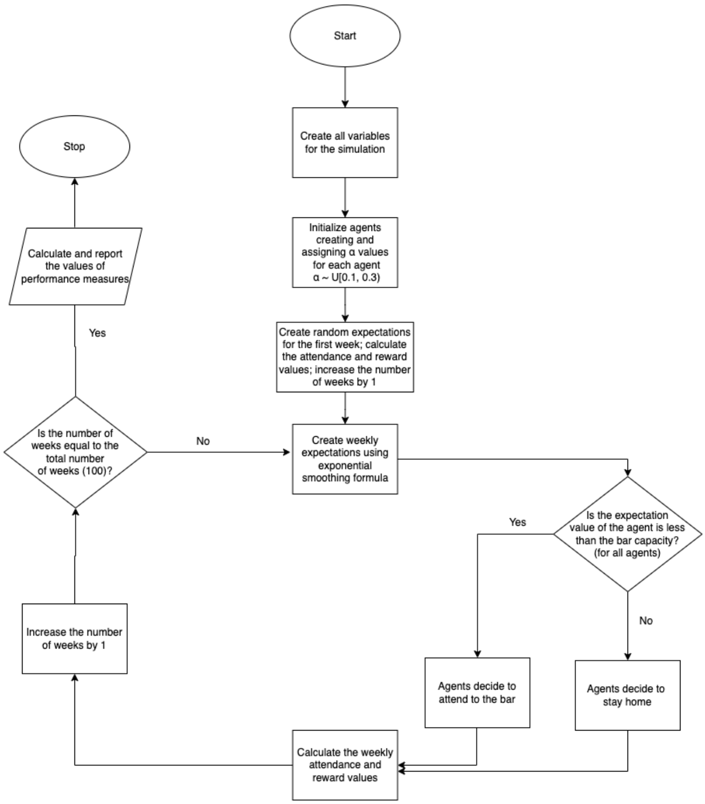

Figure 4. Flowchart of the Algorithm for Type 3 Agents

3. Performance Measures

The comparative analysis will be conducted by using two performance measures, mean attendance and standard deviation of attendance. As Arthur (1994) stated, we expect to observe mean attendance to converge to the bar capacity which is 60. Also, an aggregate behavior with a low standard deviation is perceived to be good because as we get closer to 60, a smaller number of agents make incorrect decisions. Comparatively, the agent type with a mean attendance converging to 60 faster and with a lower standard deviation of attendance creates better behavior on the aggregate level.

3.1. Mean Attendance

The weekly attendance values are calculated by counting the number of agents who decide to attend the bar. The mean of the weekly attendance values is obtained by dividing the sum of the attendance values by the total number of simulated weeks. The weekly attendance and mean attendance equations can be expressed as

$$\text{Attendance}_s = \sum_{i=0}^{n} \text{Decisions}_i \tag{3}$$

where i is the counter variable for the number of agents

and s is the counter variable for the number of weeks.

$$\text{MeanAttendance} = \frac{\sum_{s=1}^{TotalWeeks} \text{Attendance}_s}{\text{TotalWeeks}} \tag{4}$$

Arthur (1994) states that mean attendance always converges to 60 which is the bar capacity value. Note that the mean attendance values are continuous, and the range of possible values is between 0 and 100. Assume that the total number of simulated weeks is 52. If nobody attends the bar for 52 weeks, the mean attendance becomes 0, and if all agents attend the bar every week for 52 weeks, the mean attendance becomes 100.

3.2. Standard Deviation of Attendance

We introduce the mean attendance as a performance measure in the EFBP. Arthur (1994) builds his arguments based on the mean attendance statistics. However, mean attendance values are not sufficient to comment on the success of the different expectation models in the EFBP. The standard deviation of attendance values is also used to compare different models' performances (Fogel et al., 1999; Garofalo, 2006; Rand and Stonedahl, 2007). The equation of the standard deviation of attendance can be written as

$$\text{Standard Deviation of Attendance} = \sqrt{\frac{\sum_{s=1}^{TotalWeeks}(\text{Attendances}-\text{MeanAttendance})^2}{\text{TotalWeeks}-1}} \quad (5)$$

where s is the counter variable for the number of weeks.

In the EFBP, high standard deviation causes a worse-performing expectation model because as we diverge away from 60, a greater number of agents make incorrect decisions. Therefore, we aim for a low standard deviation with convergence in the mean attendance value toward the bar capacity, which is 60 people. If all attendance values are the same, we obtain 0 as the standard deviation of attendance, and if the attendance value is zero for half of the time while it is 100 for the other half of the time, the standard deviation of attendance becomes 50. Therefore, the range of possible values for the standard deviation of the attendance is between 0 and 50.

4. Comparison and Simulation Results

First, we introduce the algorithms for three different agent types, and then we examine the results of each agent type. Type 1 agents use random expectations in making their decisions to attend or not to attend the bar. The mean attendance and standard deviation of attendance values are equal to 60.25 and 5.004, respectively, for the representative simulation run given in Figure 5. The output graph in Figure 5 shows that behavior of Type 1 Agents creates a low standard deviation of attendance and have a converging mean attendance to 60, which indicates high number of correct decisions as a population.

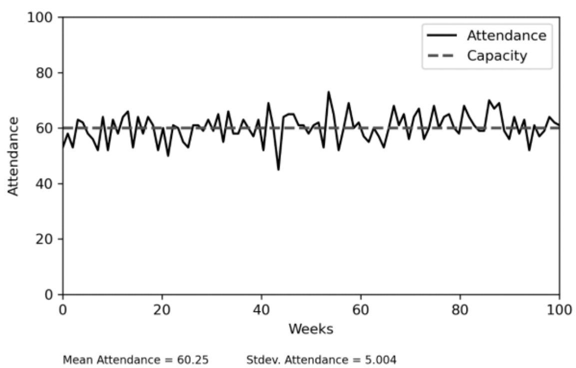

Figure 5. A Single Run For Type 1 Agents

We use the bag of strategies that Arthur and Garofalo state to create the expectations, in other words we use the same predictors with Arthur and Garofalo to create Type 2 agents. There are total 200 strategies (m = 200) and each agent can have 6 strategies (k = 6). The error term for switching strategy is calculated with an exponential smoothing formula where the weight of correction is 0.2. The mean attendance and standard deviation of attendance values for a single representative run are 60.54 and 9.096 as it is shown in Figure 6. These results are consistent with the Garofalo's NetLogo model's outputs as well which has mean attendance value of 60.01 and the standard deviation of 8.73 for 100 weeks (Garofalo, 2006). The difference in the standard deviation is caused by the strategy types and randomness.

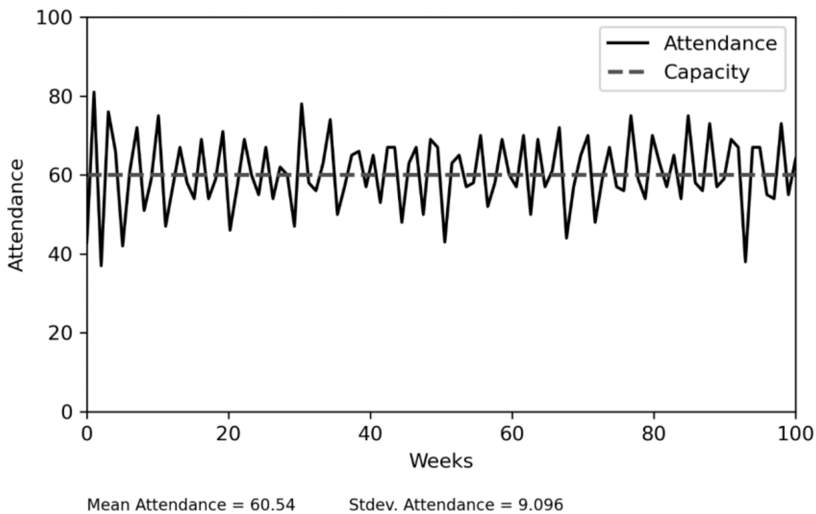

Figure 6. A Single Run For Type 2 Agents

Our third expectation model contains boundedly rational agents with adaptive learning. The agents create their weekly expectation values using an exponential smoothing formula on new attendance values. Each agent has an individual alpha value which indicates the weight of the new attendance value on the expectation function. The alpha value is randomly determined between 0.1 and 0.3. If all the agents used the same alpha values, they would all have one single expectation model which cause all agents to attend or not to attend the bar at the same time (Figure 3). We introduce Type 3 Agents aiming to see the effect of adaptive learning process in the EFBP. We expect to see a "better performance" by Type 3 Agents caused by the learning process. Although each agent has an individual expectation formulation with different alpha values, unfortunately we obtain some sort of commonality of expectations resulting in a deterioration in the overall performance. Note that we also tried to assign alpha values between theoretical limits (0-1). We do not observe any significant difference in the behavior regardless of the change on alpha values. One representative simulation result for Type 3 Agents is given in Figure 7.

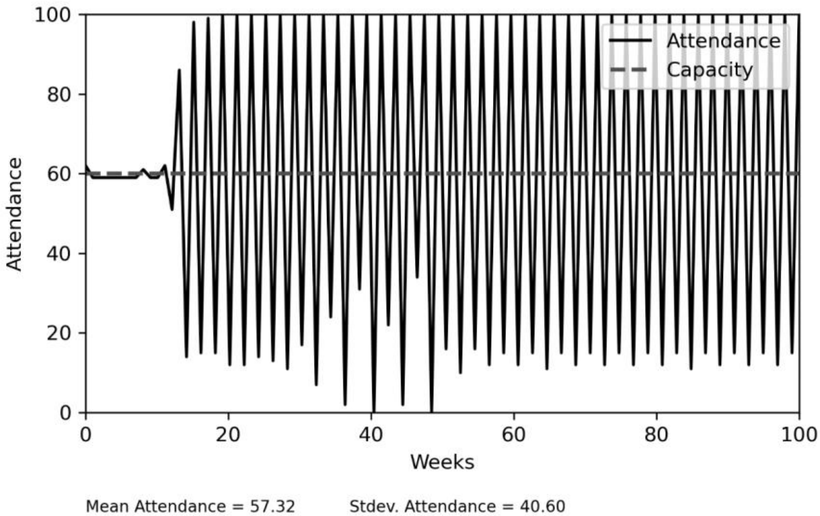

Figure 7. A Single Run For Type 3 Agents

Figure 7 shows that not all but most of the agents give the same decision on the same weeks. The mean attendance is 57.32 and the standard deviation is very high, 40.60, which indicates that the performance of Type 3 Agents is very poor in terms of utilization of the bar. We see that the Type 3 Agents behave very similar to the "deductive reasoning agents" after a transition phase. Arthur claimed that if the agents in the EFBP used deductive reasoning, in other words the same expectation models, the decisions would not differ, and they all choose to attend or not to attend the bar at the same time. We know that Type 3 Agents use inductive reasoning to form their expectations. Even though they use inductive reasoning and an adaptive learning mechanism, the behavior of Type 3 Agents looks very similar to a deductive reasoning decision-making mechanism, and it causes a poor performance in the EFBP. The standard deviation of Type 1 Agents (Figure 5) is less than the other two types of agents (Figure 6 and 7). The output of Type 1 Agents fluctuates around the value 60 with a lower standard deviation in terms of weekly attendance values. Therefore, we conclude that the total number of correct decisions made by Type 1 Agents is higher than the other two types of agents.

On the other hand, it is known that one single simulation run is not sufficient to conduct statistical analysis since there are elements of randomness in all of the three models The expectations are created randomly for Type 1 Agents; the strategies use random expectations if the current information in the simulation is less than the memory size of the active predictor for Type 2 Agents; and the first week's attendance is based on random expectations for Type 3 Agents. Therefore, we run the simulation models using 100 random seeds and then conduct a statistical analysis in terms of performance measures. The average performance measures of 100 simulation runs for each agent type is shown in Table 1. The length of simulation is 100 weeks for each simulation run.

Table 1.

Comparative results for three agent types

Performance Measures (Range)	Type 1 Agents	Type 2 Agents	Type 3 Agents
Average of Mean Attendance (0-100)	59.89	60.31	57.07
Average of Standard Deviation of Attendance (0-50)	5.02	8.56	41.08

As we examine the comparison table (Table 1) for the agent types, we directly recognize that Type 1 Agents perform better than the Type 2 and Type 3 Agents. The mean attendance converges to the bar capacity for Type 1 and Type 2 Agents. However, Type 1 Agents have the lowest standard deviation. In addition, we can see that Type 3 Agents' performance is far worse than the other agent types. The mean attendance of Type 3 Agents does not even converge to the bar capacity and the standard deviation value is high compared to the other two types of agents. Although each agent in the model uses an individual smoothing parameter that differs from their decision-making mechanism, the mean attendance does not converge to 60 on contrary to Arthur's argument. We claim that the behavior of Type 3 Agents "converges" to the deductive reasoning behavior (Figure 7).

5. Discussion and Conclusion

According to our study, the mean attendance of Type 1 Agents (random expectations) and Type 2 Agents ("bag of strategies") both converge to the capacity of the bar. This result is in accordance with the EFBP literature. The average standard deviation of the attendance values for Type 1 Agents is less than those for Type 2 and Type 3 Agents. The convergence to the capacity combined with the smaller average standard deviation value implies that Type 1 Agents have a better bar utilization, and, at the same time, they create the highest number of correct decisions. This finding that the agents with random expectations generate the best results is consistent with the results in the literature (Ponsiglione et al., 2015). We want to add that Type 1 Agents do not use the information of weekly attendance in creating their expectations as their expectations are purely random. This indicates that either using the information from the environment or even knowing the weekly attendance values does not improve the population's performance in the EFBP. Using the past attendance values to improve performance counterintuitively results in worse performance as demonstrated by the performances of Type 2 Agents and Type 3 Agents (adaptive learning).

The reason behind the success of Type 1 Agents as a group is the heterogeneity in their decisions. The strategy switching mechanism and individual active predictor of Type 2 Agents also provide heterogeneity in their decisions. However, some agents use the same strategy with other agents in certain weeks and this has a decreasing effect on the level of heterogeneity compared to Type 1 Agents because they tend to act in small groups. Although each agent has its own individual smoothing parameter value and individual expectations, Type 3 Agents have the lowest heterogeneity in their decisions. They tend to adaptively learn the attendance values and, as they learn, they start to reach the same decision about attending the bar or not. Adaptive learning causes these agents to act as a group after a transition phase, which decreases heterogeneity.

Sterman (1987) claim that expectations are usually represented as adaptive learning processes in system dynamics models. In other words, exponential smoothing is an inductive method that can represent the behavioral expectations of humans in a dynamic simulation model. Moreover, Arthur (1994) claims that deductive reasoning in decision-making is not valid for the agents in the EFBP and inductive reasoning is a must. Based on these two claims, when we were introducing Type 3 Agents, we were hoping to obtain improved performance and good utilization of the bar caused by the adaptive learning process. Surprisingly, in this problem, learning has a detrimental effect on aggregate performance. We also conclude that the behavior of Type 3 Agents converges to the behavior that would be expected from agents using deductive reasoning.

Contribution of the Researchers

Burak Çetiner contributed to literature review, conducting experiments, modelling, coding, and writing the article; Hakan Yasarcan supervised the study and contributed to modelling, coding, and writing the article.

Conflict of Interest

The authors have no conflicts of interest to declare.

References

Adler, J. L. & Blue, V. J. (2002), A cooperative multi-agent transportation management and route guidance system, *Transportation Research Part C: Emerging Technologies,*. 10 (5-6), 433-454. Doi : https://doi.org/10.1016/S0968-090X(02)00030-X

Arthur, W. B. (1994), Inductive reasoning and bounded rationality, *The American Economic Review,* 84(2), 406-411. Retrieved from https://www.jstor.org/stable/2117868

Arthur, W. B. (1999), Complexity and the economy, *Science*, 284(5411), 107-109. Doi: https://doi.org/10.1126/science.284.5411.10

Chakrabarti, B. K. (2007), Kolkata restaurant problem as a generalised El Farol bar problem, *Econophysics of Markets and Business Networks*, 239-246. Doi: https://doi.org/10.1007/978-88-470-0665-2_18

Challet, D., & Zhang, Y. C. (1997), Emergence of cooperation and organization in an evolutionary game, *Physica A: Statistical Mechanics and its Applications*, 246(3-4), 407-418. Doi: https://doi.org/10.1016/S0378-4371(97)00419-6

Chen, S. H. & Gostoli, U. (2017), Coordination in the el farol bar problem: the role of social preferences and social networks, *Journal of Economic Interaction and Coordination*, 12(1), 59-93. Doi: https://doi.org/10.1007/s11403-015-0150-z

De Cara, M. A. R., Pla, O. & Guinea, F. (1999), Competition, efficiency and collective behavior in the "El Farol" bar model, *The European Physical Journal B-Condensed Matter and Complex Systems*, 10(1), 187-191. Doi: https://doi.org/10.1007/s100510050843

Edmonds, B. (1998), Gossip, sexual recombination and the El Farol Bar: Modelling the emergence of heterogeneity, *IFAC Proceedings Volumes, Cambridge*, 31(16), 219-225. Doi: https://doi.org/10.1016/S1474-6670(17)40485-X

Elsner, W. (2017), Complexity economics as heterodoxy: Theory and policy, *Journal of Economic Issues,* 51(4), 939-978. Doi: https://doi.org/10.1080/00213624.2017.1391570

Fogel, D. B., Chellapilla, K. & Angeline, P. J. (1999). Inductive reasoning and bounded rationality reconsidered, *Transactions on Evolutionary Computation*, 3(2), 142-146. Doi: https://doi.org/10.1109/4235.771167

Foxon, T. J., J. Köhler, Michie, J. & Oughton, C. (2013), Towards a new complexity economics for sustainability, *Cambridge Journal of Economics*, 37(21), 187-208. Doi: https://doi.org/10.1093/cje/bes057

Galib, S. M. & Moser, I. (2011), Road trafic optimisation using an evolutionary game, *in Proceedings of the 13th Annual Conference Companion on Genetic and Evolutionary Computation*, Dublin, 519-526. Doi: https://doi.org/10.1145/2001858.2002043

Galstyan, A., Kolar, S. & Lerman, K. (2003), Resource allocation games with changing resource capacities, *in Proceedings of the Second International Joint Conference on Autonomous Agents and Multiagent Systems*, New York, 145-152. Doi: https://doi.org/10.1145/860575.860599

Gardner Jr, E. S. (1985). Exponential smoothing: The state of the art. *Journal of Forecasting*, 4(1), 1-28. Doi: https://doi.org/10.1002/for.3980040103

Garofalo, M. (2006), Modeling the El Farol Bar Problem in NetLogo, Preliminary Draft, Dexia Bank Belgium. Retrieved from http://ccl.northwestern.edu/2006/ElFarol.pdf

Hausken, K., S. Banuri, Gupta, D. K. & Abbink, K. (2015), Al Qaeda at the Bar: Coordinating ıdeologues and mercenaries in terrorist organizations, *Public Choice*, 164(1), 57-73. Doi: https://doi.org/10.1007/s11127-015-0261-z

Lustosa, B. C. & Cajueiro, D. O. (2010), Constrained ınformation minority game: how was the night at El Farol?, *Physica A: Statistical Mechanics and its Applications*, 389(6), 1230-1238. Doi: https://doi.org/10.1016/j.physa.2009.11.034

Manson, S. M. (2001), Simplifying complexity: A review of complexity theory, *Geoforum,* 32(3), 405-414. Doi: https://doi.org/10.1016/S0016-7185(00)00035-X

Ponsiglione, C., Roma, V., Zampella, F. & Zollo, G. (2015). The fairness/efficiency issue explored through El Farol bar model, *Scientific Methods for the Treatment of Uncertainty in Social Sciences*, 309-327. Doi: https://doi.org/10.1007/978-3-319-19704-3_26

Rand, W. & Stonedahl, F. (2007). The El Farol bar problem and computational effort: Why people fail to use bars efficiently, Northwestern University, Evanston, IL. Retrieved from https://ccl.northwestern.edu/papers/2007/Rand&Stonedahl_ElFarolBar.pdf

Sellers, M. W., Sayama, H. & Pape, A. D. (2020), Simulating systems thinking under bounded rationality, *Complexity*, 2020, 1-12. Doi: https://doi.org/10.1155/2020/3469263

Simon, H. A. (1980). *Utility and Probability: Bounded Rationality*, London, UK: Palgrave Macmillan.

Sterman, J. D. (1987). Systems simulation. expectation formation in behavioral simulation models, *Behavioral Science*, 32(3), 190-211. Doi: https://doi.org/10.1002/bs.3830320304

St Luce, S. & Sayama, H. (2020), Phase Spaces of the strategy evolution in the El Farol bar problem, *The Conference on Artificial Life*, 558-566. Doi: https://doi.org/10.1162/isal_a_00339

Wilensky, U. & Rand, W. (2015), *An Introduction to Agent-based Modeling: Modeling Natural, Social, and Engineered Complex Systems with NetLogo*, Cambridge, UK: MIT Press.