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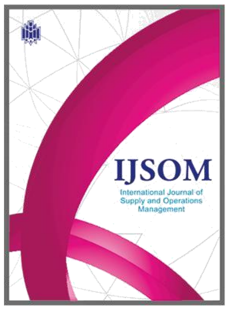

The Comparison of Neural Networks' Structures for Forecasting

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Abstract
This paper considers the application of neural networks to demand forecasting in a simple supply chain composed of a single retailer and his supplier with a game theoretic approach. This work analyses the problem from the supplier's point of view and the employed dataset in our experimentation is provided from a recognized supermarket in Morocco. Various attempts were made in order to optimize the total network error and the findings indicate that different neural net structures can be used to forecast demand such as Adaline, Multi-Layer Perceptron (MLP), or Radial Basis Function (RBF) Network. However, the most adequate one with optimal error is the MLP architecture.

Keywords: Neural networks; Artificial intelligence; Supply chain management; Information sharing; Demand forecasting; Game theory.

1. Introduction

Since the relationships between supply chain (SC) members have an important influence on the whole supply chain performance, "the research focus in supply chain management, recently, has shifted from inter-functional to inter-organizational integration and coordination" (Jain & Dubey, 2005). Many researchers, such as (Cachon, 2003) or (Gomez-Padilla, 2005), studied SC coordination to manage interdependencies among its members for approaching a decentralized system in order to work together and act in way that guaranties the alignment of the plans and objectives defined mutually as a centralized system. Different coordination mechanisms are presented in the literature (Arshinder, Kanda, & Deshmukh, 2008). This paper focuses on coordination among a two-echelon supply chain of a single retailer and his supplier by sharing demand information, and more precisely, on how to predict demand level using different neural network models in case no information is provided.

This paper is structured as follows: The first section is dedicated to the literature review and the definitions of different key concepts in our research field. Then, in the second section, the problem statement and the proposed solution are presented. Finally, the third part describes and analyses the numerical experimentations.

1.1. Definition of basic concepts

1.1.1. Information sharing in supply chains: Game theory approach

"Game theory is a bag of analytical tools designed to help us understand the phenomena that we observe when decision-makers interact" (Osborne & Rubinstein, 1994). This theory was first introduced in the 40's (Morgenstern & Neumann, 1944), it is concerned with the analysis of situations of conflict as well as of cooperation where two or more decision makers, called players affect each other's payoffs. In order to apply game theory, two assumptions (Colman, 1998) must be made: (a) rationality of players in the sense of always seeking for the maximum of their own expected utilities, and (b) common knowledge where each player take into account the information he has on the other player's strategies (Schotter, 1996).

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Games can be categorized into two sets: non-cooperative games and cooperative games. In the first category, communication or collaboration among players are not allowed in any way. However, in the second category, players are allowed to adopt negotiations and agreements in solving out the problem.

1.1.2. Information sharing as a cooperation tool

In this case study, sharing information as a cooperation mechanism means that retailer and supplier act in a cooperative manner and exchange demand information and action plans in order to align their forecasts for capacity and long-term planning. However, by revealing his private information, retailer could lose the benefit of negotiating future prices. Therefore, sharing information depends on whether it increases the supply chain's performance (Ha, Tong, & Zhang, 2010).

Information sharing in supply chains has many obstacles (Lee & Whang, 2000) such as the confidentiality, rapidity, trustworthiness, and most importantly accuracy of the provided information. Thus, and for the sake of all supply chain partners, trust and cooperation are two of the most important ingredients.

We are studying a basic SC of a single retailer (R) having an imperfect and private information about demand and his supplier (S) and focusing on the supplier's point of view. In a game theoretic context, this can be interpreted as a game of two players (retailer, supplier) having two strategies (share, not share) for (R) and (trust, distrust) for (S). Our study focuses on the supplier's point of view. More details about the game's structure as well as the payoff matrix are given in the following section. The implementation of the neural networks of forecasting for finding the equilibrium of the game is not included in this work. In this paper, we are more interested in modeling our game and finding the best neural networks structure for demand forecasting when no information is shared by the retailer.

2. Artificial Neural networks for forecasting

2.1. Related studies

Since the artificial neural networks (ANNs) are able to learn, several research projects are found to anticipate some costly calculations. For example, in sales, it is possible to predict the upcoming requests that provide a more accurate vision of production or stock level (Slimani, ElFarissi, & Achchab, 2015): (Borade and Bansod,2011) made a comparison of neural network forecasts on the basis of costs and profits in supply chain using three multi-criteria decision-making tools for evaluation. The results indicated that this method helps companies save money and improve their profitability by reducing supply chain costs.

(Doganis, Alexandridis, & Panagiotis, 2006) Present a complete framework that can be used for developing nonlinear time series sales forecasting models and apply a combinatory technique of two artificial intelligence methods, namely the RBF (Radial Basis Function) neural net architecture and a specifically designed genetic algorithm (GA) for forecasting sales data of fresh milk. Other researchers applied ANNs with fuzzy systems in order to predict demand in supply chains, the results show that adding fuzzy logic to neural networks learning ability gives more accurate predictions. (e.g. (Chang & Wang, 2006), (Gumus, Guneri, & Keles, 2009), (Wang, Chen, Wang, & Lin, 2006)).

Since ANN algorithms have the potential of accommodating the non-linear data to capture the subtle functional relationships among empirical data, (Kumar, Herbert, & Rao, 2014) use ANN for demand forecasting so that demand and supply are in balance by fulfilling customer's demand and reducing excess inventories. They also present a comparative analysis of different training methods of neural network using the results obtained from the demand-forecasting model.

(Efendigil, Önüt, & Kahraman, 2009) Present a comparative analysis between ANN's models and adaptive network-based fuzzy inference system (ANFIS) to forecast demand of future period with incomplete information. Using real-world data for 96 months from an industrial company active in durable consumer goods Turkey of three retailers. Through their experimentations, the authors demonstrate that ANFIS method gives closer forecasted values than the ANNs technique.

ANN is utilized in this work to predict future demand based on previous information. This case scenario is adopted by the supplier when no information is shared or when the information shared by the retailer is not trustful.

Different structures of neural networks are used in the literature, such as Adaline, MLP and RBF. But the most commonly used structure of neural nets is the MLP model. This architecture shows the best results for demand forecasting.

2.2. Artificial Neural network

2.2.1. What is ANN?

A neural network is composed of at least two components, i.e. neurons and the connections between them known as links. The functioning of biological human neurons (McClelland, Rumelhart, & Hinton, 1986) (Luger & Stubblefield, 1993) that receives a signal and then emits an output signal after his activation inspires neural networks (see Figure 1). In the biological neuron, dendrites transport the electrical signals sent from other neurons to the cell body and the output electrical signals are directed through the axon to other neurons. Analogous to this biological functioning, artificial neuron is activated after receiving signals (inputs) from other neurons. These signals are summed and delivered through an activation function, then the result value (output) is sent to the other neuron.

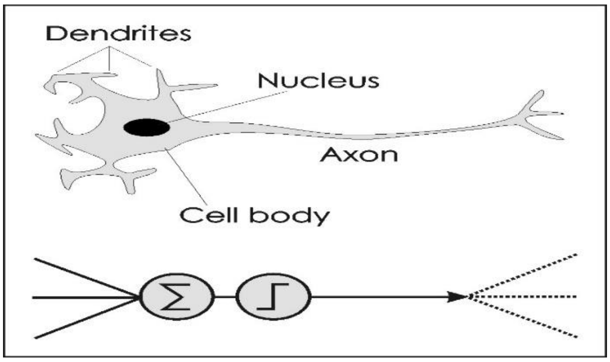

Figure 1. Graphic comparison between biological neuron and artificial neuron

With the capacity of learning and responding to issues such as the problems of analysis, diagnosis or prediction, the human neural network contains approximately 10^{11} neurons and trillions of connections between them. In computer science terms, this is translated into ANN (Rennard, 2006) which contains layers of interconnected neurons and has the ability of learning, calculating, or forecasting. In general, ANNs are capable of responding to problems relating to what it has been learned before, as they are able to program themselves. This is what we call the supervised learning (El Farissi, Azizi, & Moussaoui, 2012).

ANN consists of several interconnected layers where each layer contains more neurons. There are three types of layers: The input layer (or predictors) that receives an external input data, the output layer used to return the result(s), and the hidden layer containing neurons helping to obtain a better result. At the beginning of the network's construction, the number of neurons in the input and output layers are fixed, but there is no rule for determining the number of hidden layers or their neuron's number. The network structure depends on different parameters such as the number of hidden layers, the existence/or non-existence of bias neuron, and the chosen learning rate. Therefore, the train and test method is adopted to choose the best topology that returns better results.

Unlike the traditional forecasting methods, neural networks allow complex nonlinear relationship between inputs and outputs. (Yu, Choi, & Hui, 2011) Demonstrate that ANNs are more efficient and effective than the other traditional forecasting techniques.

A neural network is composed by at least two components, neurons and the connections between them known as links. This concept is inspired from the human neuron that receives a signal then emits an output signal after his activation. With the ability of learning, calculating and forecasting, ANN is capable of solving problems based on the learning skills, also called supervised learning (ElFarissi, 2013).

ANN is utilized in this work to predict future demand based on the previous information. This case scenario is adopted by the supplier when no information is shared or when the information shared by the retailer is not trustful.

Different structures of neural networks are used in the literature, such as Adaline, MLP, and RBF).But the most commonly used structure of neural nets is the MLP model. In our previous work, this architecture shows the best results for demand forecasting.

3. Problem statement and proposed solution

3.1. Uncertainty and forecasting

Accuracy, ease of use, and flexibility are the ideal blend for demand planning. However, the ultimate goal of any successful SC businesses is to find the balance between satisfying consumer's demand while minimizing their stock and avoiding excess inventory, due to the discerning and the unpredictable behavior of customers, it is a challenge to predict and project consumer's demand in the future. That is why forecasting is one of the commonly used methods to decrease demand uncertainty in supply chains.

3.2. Neural nets for demand forecasting

Quantifying information with accuracy is a hard, but not an impossible task to do. As a proposed solution, this work uses the artificial intelligence of neural networks to reduce demand uncertainty between a retailer and a supplier. In the realm of game theory with a cooperative approach, this can be projected as a game of two players, i.e. a single retailer and a single supplier

3.3. Introducing the game with neural nets

3.3.1. Game's description

As mentioned previously, we are studying a simple form game of two players, aiming to provide a decision making tool for the supplier. We assume that each player has two strategies as explained in table 1 below:

Table 1. Player's strategies

Player	Strategy	Meaning
Retailer	Share	(R) shares his sales level (demand information) with (S)
	Not share	(R) withholds his sales information from (S) and this one employs ANN to forecast demand
Supplier	Trust	(S) trusts information provided by (R) and takes it into account to calculate his production level
	Not trust	(S) does not trust information shared by (R) and uses ANN for demand forecasting

3.3.2. Players' expected profits

- Retailer's expected profit

Retailer's profit = Sales revenue – Purchasing cost – Shortage cost – Production cost – Information sharing cost

$$\pi_r = E[(p - r - C_r)\min(N, D) - b_r\,(D - N)^+ - C_{info}]$$

Where:

$(x)^+ = \max(0, x)$

Purchasing cost

$C_{purchasing} = r\,min(N, D)$

Shortage cost

$C_{shortage(r)} = b_r\,(D - N)^+$

Production cost

$C_{production(r)} = C_r min(N, D)$

Information sharing cost

$$C_{info} = \begin{cases} \alpha & if\ information\ is\ shared \\ 0 & if\ no\ information\ is\ shared \end{cases}$$

Where $\alpha > 0$

- Supplier's expected profit

Supplier's profit = Sales revenue – Production cost – Shortage cost – Cost related to unsold product

$$\pi_s = E[r\,min(N, D) - C_s.N - b_s\,(D - N)^+ - h_s\,(D - N)^+]$$

Production cost

$C_{production(s)} = C_s.N$

Shortage cost

$C_{shortage(s)} = b_s\,(D - N)^+$

Cost related to unsold products

$C_{unsold(r)} = h_s(N - D)^+$

3.3.3. Notations

The following notations are utilized in our formulation model:

π_r : Retailer's profit (difference between incomes and spending)
π_s : Supplier's profit
D: Market demand of the product during the current period
T: Length of each period
Q: Ordered quantity to the supplier per period T
r: Unit price with which the retailer buys the product from the supplier

p: Unit selling price of the product on the market by the retailer; (where r < p)
c_r : Unit production cost of the retailer
b_r : Unit breakdown cost of the retailer
c_s : Unit production cost of the supplier
b_s : Unit breakdown cost of the supplier
N: Supplier's replenishment level, it is the quantity in stock at the end of each period before demand arrives
h_s: Cost of unsold unit paid by the supplier
h_r: Cost of unsold unit paid by the retailer

3.3.4. Payoff matrix

All possible combinations of the players' actions and their possible outcomes are presented in a matrix called the decision table or the payoff matrix. Analyzing this matrix in order to determine the optimal strategies for all players is the goal of game theory. The payoff matrix of our game is defined as follows:

		Supplier	
		Trust	Not trust
Retailer	Share	(π_r^*, π_S^*)	(π_r^o, π_S^o)
	Not share	(π_r', π_S')	(π_r', π_S')

In a typical form, it is a two-by-two matrix (Slimani-a & Achchab, 2014) (Slimani-b & Achchab, 2013) with each square divided in half, with one half for each one of the two players involved. Having:

Table 2. Player's strategies

Players	Strategies	Demand
Retailer (R) Supplier (S)	(share ,trust)	D^*: demand when (R) shares information and (S) trusts it
	(share, not trust)	D^o: demand when (R) shares information and (S) does not take it into account
	(not share ,trust)	D': demand when (R) does not share information and (S) trusts it
	(not share, not trust)	D': demand when (R) does not share information and (S) does not trust it

4. Numerical examples

4.1. Methodology

Without accurate business information and, more precisely, demand information, all supply chain resources are useless. Since planning production, inventory, distribution policy, and even marketing would not be an easy task for managers. Therefore, the accuracy of demand forecasts in a supply chain management is an important key to competitiveness.

In this paper, various ANN models were presented and utilized to predict future demand of customer's product based on previous information. The training and validating data were provided from a recognized supermarket in Morocco. In our experimentation, we have tried different neural networks structures like Adaline, NoProp, Perceptron, MLP and RBF aiming to compare their results and come up with the best model with the optimal error. To predict the demand of the fourth week of a month, the networks are powered by real values of the first three Mondays (d, d+7 and d+14), for example, then the value of the fourth Monday (d+21) is forecasted. Forecasts of the other days of the week are obtained by following the same method.

4.2. Results

The network is trained using real data from a supermarket in Morocco. The training dataset contains 77 recordings and the test dataset contains 60 recordings. In our experimentation, networks are powered by three inputs and return one output. The following table represents a preview of these data:

Table 3. Preview of preprocessed inputs and outputs

Input 1	Input 2	Input 3	Output
0.3582	-0.1044	0.3432	0.7094
-0.3283	-0.6268	-0.5074	0.1880
-0.5074	-0.5970	-0.5671	0.2136
-0.4776	-0.1641	-0.2089	0.1965
-0.4029	-0.4925	-0.5074	0.1965

Initially, we present the Mean Squared Error (MSE) of different ANN architectures obtained during the training and the testing phases.

- Adaline
  - Training

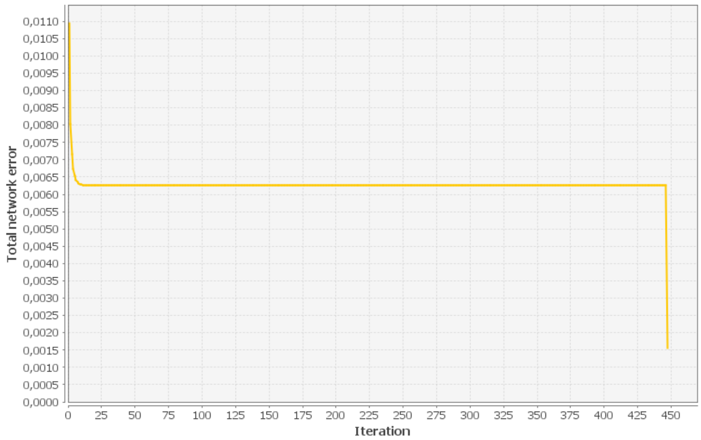

Figure 2. MSE training graph of Adaline

- Test

Total MSE = 0.060704

Table 4. Preview of testing results: Adaline

Output	Desired	Difference
2403,4224	2375,904	-27,5184
2267,796	2448,0696	180,2736
2234,9424	2400,0528	165,1104
2400,6144	2400,0528	-0,5616
2269,2	2975,9736	706,7736
1982,784	2207,9856	225,2016
1937,0136	2232,1344	295,1208
2706,4056	2423,9208	-282,4848
2127,396	2448,0696	320,6736
3448,56	3191,9088	-256,6512

N.B:
The number of results obtained with an absolute difference ≥ 300 is 36

- NoProp
  - Training

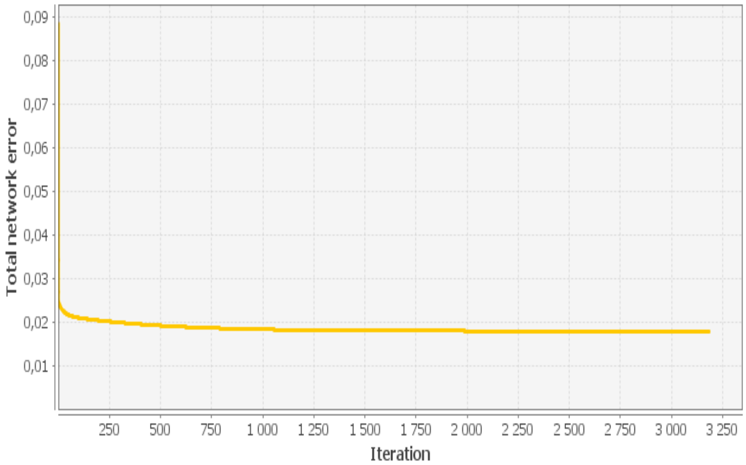

Figure 3. MSE training graph of NoProp

- Test

Total MSE = 0.271268

Table 5. Preview of testing results: NoProp

Output	Desired	Difference
2034,732	3839,995	1805,263
510,5496	2375,904	1865,354
1074,115	2400,053	1325,938
598,7208	2400,053	1801,332
2759,477	4296,014	1536,538
2997,314	2975,974	-21,3408
420,6936	2207,986	1787,292
379,416	2232,134	1852,718
1176,046	2423,921	1247,875
525,1512	2448,07	1922,918

N.B:
The number of results obtained with an absolute difference ≥ 300 is 56

- Radial Basis Function (RBF)
  - Training

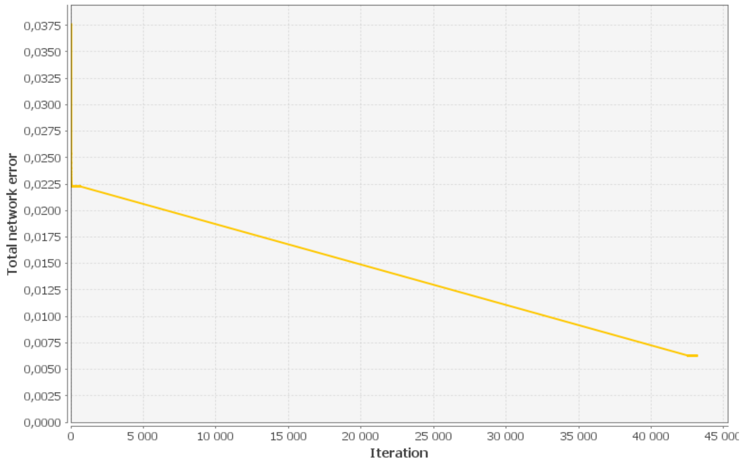

Figure 4. MSE training graph of RBF

  - Test

Total MSE = 0.209663

Table 6. Preview of testing results: RBF

Output	Desired	Difference
1927,466	2375,904	448,4376
1928,59	2448,07	519,48
1981,38	2400,053	418,6728
1834,802	2232,134	397,332
2033,89	2423,921	390,0312
1892,366	2448,07	555,7032
1431,012	4367,899	2936,887
1635,715	3191,909	1556,194
2008,056	2111,952	103,896
1992,612	2111,952	119,34

N.B:
The number of results obtained with an absolute difference ≥ 300 is 48

- Perceptron
  - Training

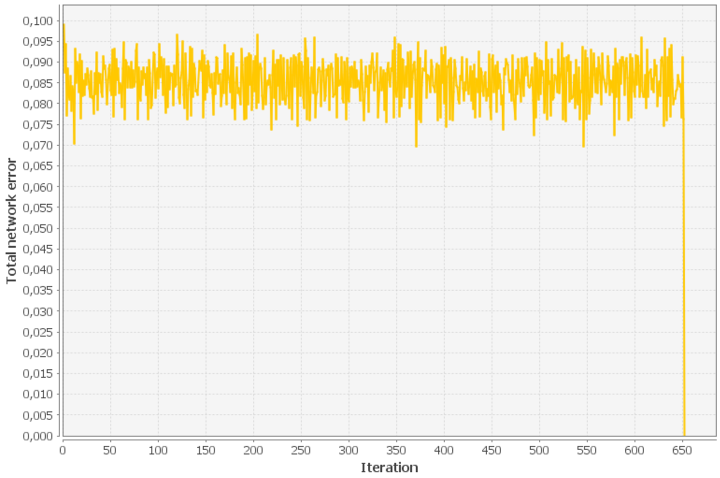

Figure 5. MSE training graph of Perceptron

- Test

Total MSE = 0.191204

Table 7. Preview of testing results: Perceptron

Output	Desired	Difference
1848	3839,995	1991,995
1848	2375,904	527,904
1848	2448,07	600,0696
1848	2400,053	552,0528
1848	2400,053	552,0528
1848	4296,014	2448,014
1848	2975,974	1127,974
1848	2207,986	359,9856
1848	2232,134	384,1344
1848	2423,921	575,9208

N.B:

The number of results obtained with an absolute difference ≥ 300 is 51

- Multi Layer Perceptron
  - Training

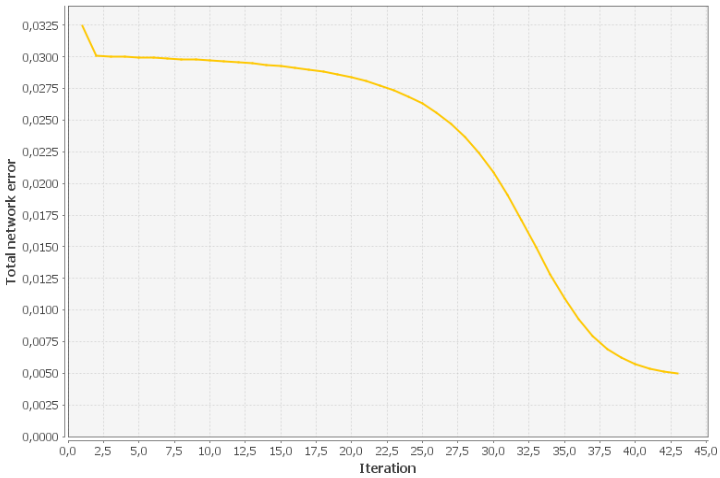

Figure 6. MSE training graph of MLP

- Test

Total MSE = 0.098359

Table 8. Preview of testing results: MLP

Output	Desired	Difference
3570,989	3839,995	269,0064
2363,549	2375,904	12,3552
2332,661	2448,07	115,4088
2566,848	2400,053	-166,795
2377,87	2400,053	22,1832
3747,612	4296,014	548,4024
2351,755	2207,986	-143,77
2351,474	2232,134	-119,34
2663,724	2423,921	-239,803
2380,678	2448,07	67,392

N.B:
The number of results obtained with an absolute difference ≥ 300 is 26

5. Analysis

We can easily conclude from the obtained results that even if the structure Adaline has the least MSE in the testing phase, the best neural net structure is the MLP. This is due to the difference between the obtained output and the desired one. In fact, with Adaline, the number of results with difference ≥ 300 is 36. However, with the MLP structure we have got only 26 recordings.

6. Conclusion

In this paper, various neural network architectures are implemented to test their ability to forecast demand of a supermarket in Morocco. We concluded that the MLP structure is the most adequate one in this context. For future studies, we propose to add a preparative phase before the forecasting phase using another technique such as neural networks with classification capability or fuzzy logic to guarantee the consistency and the homogeneity of the input data. Another perspective of this study consists of implementing the obtained results in the payoff matrix in order to find the equilibrium of the game.

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