Journal of Mathematics and Modeling in Finance (JMMF)
Vol. 2, No. 1, Winter & Spring 2022
Research paper

Assets Supply Demand Physical Equilibrium in Financial Market by Artificial Neural Network

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Abstract:
In this article supply demand based on prices volumes are extracted as measure of swaps between two or more indexes by neural network for recommend Market Makers to increase performance of Large Traded Volumes in real time Markets Quotes. Neural network are widely applicable tools for develop operators performances in financial market applications. In classic economy when an equilibrium was Unbalanced must be a side of supply or demand was over than other one.in more indexes decisions for check balance condition between more than two indexes in real time market a neural network classification trigger is good suggestion. other methods such as indicators oscillators and numerical methods and statistical methods were been slow. The latency of candle data in clients solved by time stamp in log file and export of these triggers can draw by graphical Line or shape in data.an equilibrium point as middle of these balances for pairs of indexes are connected with triangle shape.

Keywords: Financial Equilibrium, Financial Physics, Neural Network, Supply, Demand.
Classification: C68, G10, C45.

1 Introduction

There is a lot of discussion in financial neural networks and its applications.Some of application is regression and classification.The importance of research in this topic is needed to improvement of financial market tools for better support customers and client in brokers for golden decision next strategy [1] .In the subject of our article, the usage of classical equilibrium in all financial market indicators has been examined. Excess supply leads to lower prices and excess demand leads to higher prices in a financial index.In convexity language based on kernel smoothing and classification of convex and concave [10] we need more convexity for computation. From the direction of the candle formed at the end of the time frame, it must be concluded whether supply has outpaced demand or vice versa [2]. Declining trading means that the momentum is declining, but in random and algorithmic trading markets, this may be a technique implemented by an algorithmic machine to stimulate supply or demand in the audience. Therefore, the study of the classic

[1]Corresponding author
Received: 16/03/2022 Accepted: 16/08/2022
http://dx.doi.org/10.22054/jmmf.2022.67067.1052

general equilibrium of the market can be between indicators as a meter to calculate the conversion status between the two indicators [7]. Swings that swell and empty quickly Swings that swing gently, swing, or swing Two different types of financial physics swing, and swings that show impulsive behaviors pose a greater risk to converters(5). Because it brings abnormal physical energy to supply and demand(4) [3]. A classifier-learning neural network allows the financial market operator to compare and display the classical equilibrium between indices over different time frames [4]. In the form of a polynomial, the product of the weight of the price of each candle bar is obtained(7). Supply has an imbalance [8], and on the contrary, whenever the price of each candle in the volume of the candle has a variance less than the average of the variance of all candelas compared to its previous time [6], that is, the demand balance has an imbalance(10) Although mathematically and neurally it is possible to compare the equilibrium of one time frame of one index with different time frames of other indices [5], but due to the random nature of the queues in this general equilibrium [9], it is not possible to draw logical conclusions from it. Our motivation is developing neural network in to classification for gradient of market forces. In the second chapter, the principles of the equation of equilibrium and supply and demand are examined In the third chapter, the implementation of equilibrium by the classifier [11] and multilayer neural network In the fourth chapter, the method of comparing experimental samples and conclusions are reviewed.

2 principles of the equation of equilibrium and supply demand

Suppose the dynamics of two shares follow the following equation.

$$ds_1(t) = \mu_1(t)s_1(t)dt + \sigma_1(t)s_1(t)dw_1(t) \tag{1}$$

$$ds_2(t) = \mu_2(t)s_2(t)dt + \sigma_2(t)s_2(t)dw_2(t) \tag{2}$$

that W_1, W_2 are white noise of stochastic driven(Winner,Levy,etc). Suppose the trading volume of two shares follows the following equation

$$dV_1(t) = \mu_{V_1}(t)V_1(t)dt + \sigma_{V_1}V_1(t)dP_{V_1}(t) \tag{3}$$

$$dV_2(t) = \mu_{V_2}(t)V_2(t)dt + \sigma_{V_2}V_2(t)dP_{V_2}(t) \tag{4}$$

and Poisson Distribution Function that is from queue of traders on volume index.

$$p(V, \lambda_i) = \frac{e_i^{\lambda}\lambda_i^{V}{}_i}{V_i!} \qquad \forall V = 0, 1, 2, 3, ..., i = 1, 2 \tag{5}$$

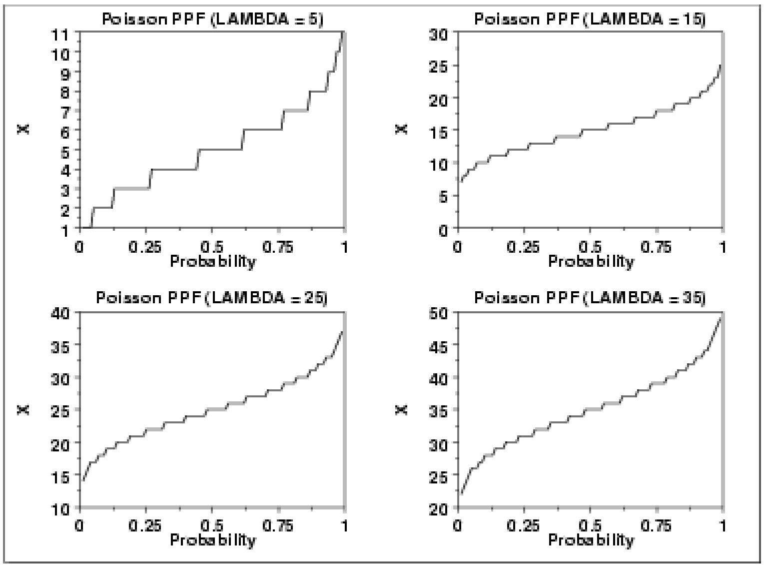

Figure 1: Poisson Distribiuation for Volume with Different Lambda

The construction of the total value index for the whole becomes two shares the following formula

$$V_{Total_{1,2}}(t) = s_1(t) \times V_1(t) + s_2(t) \times V_2(t) \tag{6}$$

And for the total market value follows

$$V_{Total} = \sum_{i=1}^{N} \prod_{i=1}^{N} s_i V_i \tag{7}$$

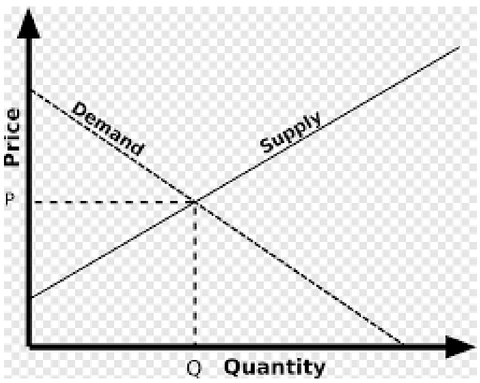

Figure 2: Classic 2 asset Equlibrium Linear Curve

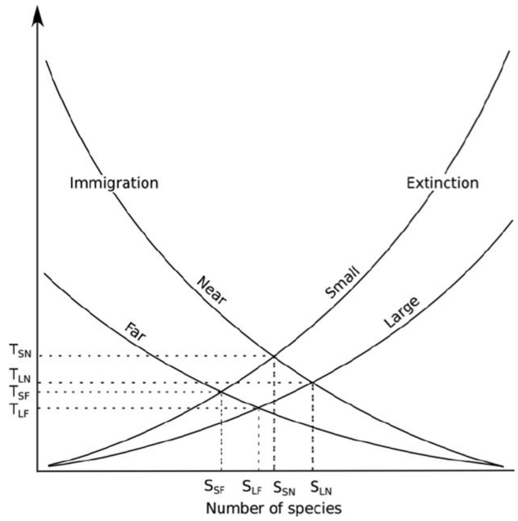

Figure 3: Classic Multi Equlibrium NonLinear Curve

Which is its mean $\frac{V_{Total}}{N}(t)$ and its total variance $\frac{\sum_{i=1}^{N}(V_i - V_{Total})^2}{N-1}(t)$. For each share, the equilibrium ratio is

$$\frac{s_i \times V_i}{V_{Total}}(t) = \frac{s_j \times V_j}{V_{Total}}(t) \tag{8}$$

for each time frame. And now if the average price ratio is multiplied by the volume to the total value per share and the ratio of this calculation to the normalized total value index is the value to the total value, since the number of this fraction will be different from the actual number observed in the Terminal Market. The variance of these two numbers is the variance of the total value of supply over demand if it is negative and vice versa, if it is positive, demand over supply has a relative dominance in that time frame.

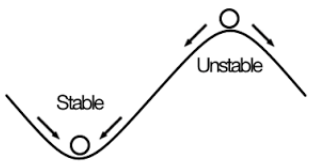

Figure 4: Classic Inertia Physical Energy

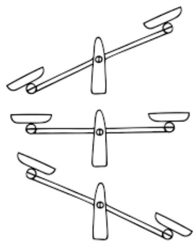

Figure 5: Classic UnEqulibrium Supply Demand Frequency

3 implementation of equilibrium by the classifier and multilayer neural network

in this section introduce an implementation of multi-layer Neural Network for pivot of flow in Time frames first input log files of assets and then create 2 row streams of Volumes and Price for extend these methods we can compare adjust-close with open low high price in last candle and from difference between these stream variables find last negative or positive up down candle. (9) second layer is designed for compare trigger of Total variance of asset in each time frame with local variance of real time candle bar if value is positive than (8) triangle pivot shape draw else nothing if is equal then fix price triangle pivot shape drawn.

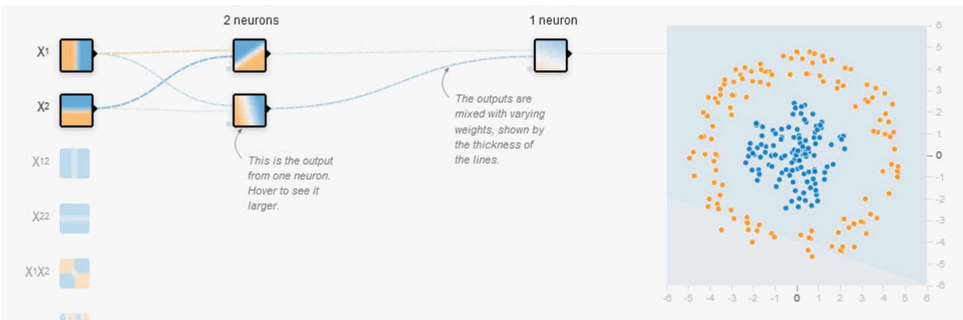

Figure 6: Classification Neural Network on VolumePrice

and last perceptron for solve percentage difference of Variance based on Total variance in each time frame for recorded and classification of level of equilibrium for each asset id in real time format for draw or log file.

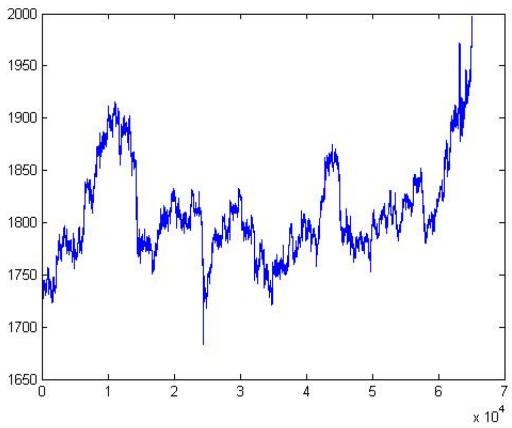

Figure 7: Asset Dynamic

4 method of comparing experimental samples and conclusions are reviewed

in this section we introduce our example of 2 asset Pivot of Flows for Sp600 Irani Nasdaq and compare comic preview of classic Equilibrium with this classifier based on normalized by total variance . as shown (8) triangles shapes shown classic physical Equilibrium based on confidence interval of Equilibrium Value for example between Gold price and USD ,etc.at the end of chart forces are silent and after it market go to very forced power that hasn't any Equilibrium as shown in (7).train set is 0.20% total time frame and time frame is save every 5 min in log file80 % total data for test learn Equilibrium point .all gradient force converged near 1800dollar after silent forced similar to Large Number Law. Four segment implements for separate regions of local equilibrium confidence interval of e equation between z=0-0.01 ,0.01-0.02,0.02,0.03,etc draws for colors green,blue,orange,red,etc for graphical representation in output graph as shown in (9).

$$CI = \bar{S} \pm z\frac{S}{N} \tag{9}$$

That z is normal standard distribution.

5 Conclusion

Real time Equlibirum flow pivot is good tools for extend swaps large volume trading and fast trading in brokers.Classification of Flow Gradient of Market Forces between 2 asset or more can show Swap Point of Markets.In this paper worked on General equilibrium with neural network,for continues suggest improve hypothesis and confidence intervals details for compare data of equilibrium, and generate

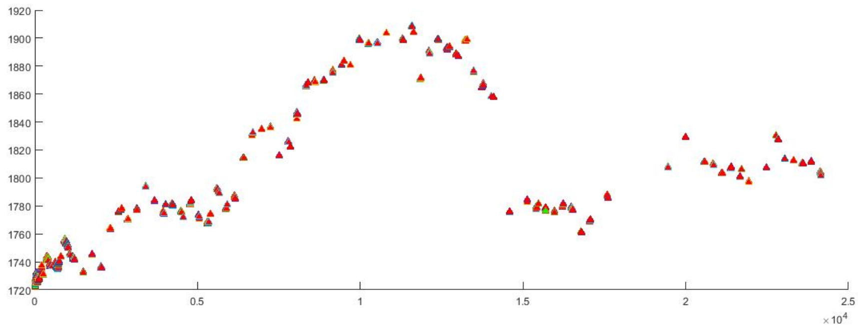

Figure 8: Classification Neural Network on Flow Gradient

Figure 9: Force Value of Volume for Equlibrium

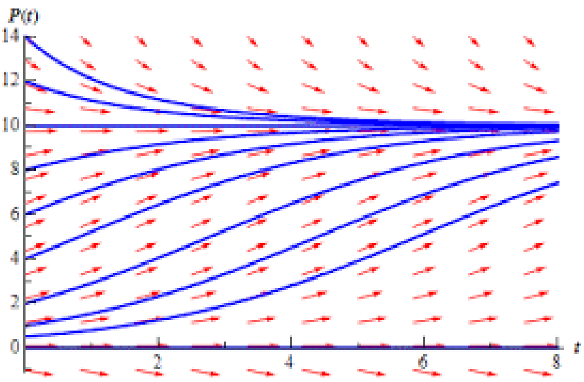

Figure 10: Classic Multi Equlibrium Flows Curve

two random asset with differents paramters for compare general equilibrium summary,also can extend to levy jump process and effect of force index in time series of equlibrium forces.

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How to Cite: Kamran Ayati[1], *Assets Supply Demand Physical Equilibrium in Financial Market by Artificial Neural Network*, Journal of Mathematics and Modeling in Finance (JMMF), Vol. 2, No. 1, Pages:87–94, (2022).