Collaborative Cognition for Commodity Price Prediction

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Abstract

There has been significant interest to predict prices for commodities (raw materials) in spot markets that are volatile as well formulate significant portion of manufacturing costs. This is an important research problem as industries spend several billion dollars in a year to procure such commodities for their business. In this paper, we present a novel approach for price prediction problem by formulating this as collaborative decision-making among autonomous agents or human experts. Following this approach, initially different autonomous agents produce predictions for the commodity leveraging their own knowledge and expertise. Then, these agents collaborate among themselves to share knowledge (full or partial) with each other towards collectively generating prediction of the commodity prices. An agents predictive performance may vary due to changes in the commodity ecosystem as well as various exogenous factors. Since predictions are generated at both an individual agent level as well as at the group level, the groups collective performance is comparatively robust and much better than initial predictions done at an individual agent level. For commodity price prediction problem, where the price is an outcome of multiple competing stakeholders in the market, our proposed collaborative decision-making framework has been observed to be a very powerful methodology in comparison to other state-of-the-art counterparts.

Key Words: Price Prediction, Statistical Modelling, Collaborative Cognition, Computing, Multi-Agent System, Cognitive Agent

1. Introduction

1.1 Overview of Price Prediction and Collaborative Cognition (CC)

Traditionally price prediction problems are treated as Time series modelling problems where the price of a commodity is modelled over time. Often, commodity prices are modelled using econometric based models leveraging market dynamics. A number of stochastic modelling techniques are often used for modelling the price of a commodity. In this paper, we discuss modelling of commodity prices through a collaborative decision-making methodology. In this case, different agents predict the price of the same target commodity using different modelling techniques leveraging different features of data. Hence, each agent has a different perception of the environment or data which they use to predict the price of the commodity. Then these agents get into collaborative decision-making phase leveraging a collaborative cognition platform. Every agent proposes the raw prediction and revises the prediction based on the proposed prediction of the other agents. Through this iterative ,collaborative decision making phase, agents themselves share their predictions with each other and become more intelligent to come up with one accurate final prediction of the commodity. Collaborative Cognition (CC) is a novelty in the domain of price prediction, allowing each agent to propose their initial predictions based on their vantage point of commodity ecosystem and eventually helping them to converge these initial predictions into singular system level commodity prediction, which is reflective of combined wisdom of all participating agents.

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1.2 Introduction to Collaborative Cognition (CC)

Collaborative Cognition (CC) is an approach wherein various domain experts from an organization come together, collaborate in a non-optimized manner, and attempt to predict prices of a commodity. Examples of these domain experts may include supply analyst, demand analyst, international trade expert(Import, Export duties, constraints etc.), domestic regulations expert (such as minimum support price (MSP) etc.), Feedstock specialist, Transportation specialist, Currency expert, Alternate Feedstock specialist, Procurement specialist etc.

At present all these experts do their analysis in a silo and then share them to typically to Procurement Lead who is left with the difficult job of collating all these numbers and translate them into buying decisions. Limitation of this approach is the centralized nature and lack of a collaboration platform where all the experts can be on-boarded and allowed to collaborate towards a price prediction which is reflective of all the wisdom available with the organization. Further, in some setups, there is a need for experts to protect information around their data sources, which further hinders collaboration among the experts.

Collaborative Cognition (CC) platform attempts to resolve problems associated with above process. It is built on cognitive technologies like Agent-based Modelling, Multi-Agent Systems, Game Theory and Machine Learning. Collaborative Cognition (CC) core engine allows all the different stakeholders (agents) to coexist, with each agent model independently generating predictive insights utilizing different analytical methodologies (Machine Learning, Time Series Analysis, Economic Modeling etc) relying on different information sources (structured, unstructured, private and public) and knowledge domains (Financial, Economics etc). Collaborative Cognition (CC) platform is then responsible for infusing wisdom extracted from all agents to predict a singular price range for the commodity. Apart from predicting price, the platform also provides a 360-Degree view around the commodity ecosystem to procurement head enabling him to make better procurement decisions.

1.3 Advantages and disadvantages of using Collaborative Cognition (CC) versus the usual modeling approaches

Here is a list of advantages of using Collaborative Cognition (CC) versus usual modelling problems:

- Software Agents: Platform allows cognitive agents to impersonate human domain experts for purposes of submitting initial predictions and participate in convergence cycle and adjusting predictions. This is a huge advantage over conventional systems where manual intervention by experts are needed at every stage, analyzing domain data (feature sets), submission of initial predictions, collaborating and correcting predictions based on other agents recommendations.

- Decentralized: No central business entity required, autonomous agents collaborate and make their own decisions in the process of convergence of initial predictions. Armed with the knowledge of current data and past performance of other agents, they may (or may not) change their initial predictions or may decide to change till an upper or lower price range. The platform facilitates all stakeholders to reach high-quality consensus decision (or predictions) in an automated fashion.

- Human Participation: Apart from Cognitive Agents, Platform allows for humans to participate in price convergence process. The inclusion of diverse agents, including human experts, has been a major design objective of the platform. Allowing humans to participate enables platform and associated agents to be built over iterations. This also serves as a good mitigation strategy and gives a technical team enough time to fine tune specific agents when their predictions go haywire.

- Wisdom of Diverse Opinions: Platform allows experts representing diverse and complex market forces to come together and ensure the final system prediction accounts for of all these forces.
- Readability: Instead of just providing procurement specialist with raw numbers, the platform provides patterns and insights, allowing a specialist to quickly understand positions of complex and dynamic market forces and make better procurement decisions.
- Accurate over longer periods of time: Platform allows for agents to keep evolving their knowledge base, reflective of correlations in the current market scenario. An agent can update their knowledge organically or inorganically by exchanging feature sets (knowledge) among themselves.
- Saves Human Time and Effort: Platform reduces the need for stakeholders to be tuned in for analyzing data streams and also in the final decision-making cycles while ensuring their preferences are captured and reflected in final decisions.

Here is a list of disadvantages of using Collaborative Cognition (CC) versus usual modelling problems:

- Agents need to be overloaded with game theory aspects in addition to the primary responsibility of generating price predictions.
- Related to above, the system requires a multi-agent platform, which can provide functionalities like managing agent lifecycle, communication between them etc., in addition to conventional technology stack of ML etc. for making price predictions.

2. Literature Survey

2.1 Prior work in the domain of price prediction

Studies involving price prediction problems have been done in the past leveraging different prediction techniques. However, the majority of the research work done so far has only considered prediction problems solely and tried to better the prediction techniques leveraging different technical approaches. In the work by Javidi, Pedsziz, Lee Goh, and Mandic (2008), complex least mean square (ACLMS) algorithms were used for complex domain adaptive filtering to solve adaptive prediction problems. To solve time series based online prediction problems Richard, Bermudez, Honeine (2009) proposed a model reduction methodology derived from kernel-based normalized LMS algorithms. There are a number of papers in the existing literature which used support vector machine (Wang, Men, Lu (2008)), prediction in mini batches (Dekel, Gilad-Bachrach, Shamir, Xiao (2012)) for solving online prediction problems. Raftery, Karny, Ettler (2010) proposed a dynamic model averaging technique for online predictions under model uncertainty. Ghani (2005) proposed methodologies to solve price prediction and insurance for online auction-based problems. Just, Rausser (1981) proposed different techniques to solve commodity price forecasting problems using large-scale econometric models. Ferraro, Rogoff, Rossi (2015) studied whether oil prices can forecast the exchange rate in the market and they presented an empirical analysis of the relationship between commodity prices and exchange rates. Borensztein, Reinhart (1994) addressed the macroeconomic determinants of commodity prices.

In this paper, authors incorporate the supply volumes of the commodities and analyzed the impact of supply volumes on commodity prices. In particular, they presented empirical results which include the output developments in Eastern Europe and the former Soviet Union. Gargano, Timmermann (2014) proposed methodologies for predicting commodity price indexes leveraging microeconomics and financial predictors. In this paper, we present price prediction methodologies for agents leveraging collaborative decision-making techniques in a collaborative cognition platform. A lot of work has been done in supply chain network, supply chain management domain leveraging multi-agent based frameworks by Jiao, You, Kumar (2006), Giannakis, Louis (2011), Labarthe, Espinasse, Ferrarini, Montreuil (2007). In this work we leverage collaborative decision-making techniques for online price prediction problems. In the next subsection, we propose a few existing works on multi-agent based platforms.

2.2 Prior work on Multi-Agent platforms

There has been extensive research work on the different types of Agents and Multi-Agent Systems (MAS). For purposes of Collaborate Cognition (CC) and price prediction platform, a Software Agent is defined as a virtual and autonomous entity capable of analyzing data sources for predicting prices of a commodity, collaborating with other agents towards a converged prediction price and learns from external data and other co-operating agents towards improving its own predictions. A pictorial representation of collaborative learning for agents is given in Figure 1 first discussed by Nwana, H. (1996).

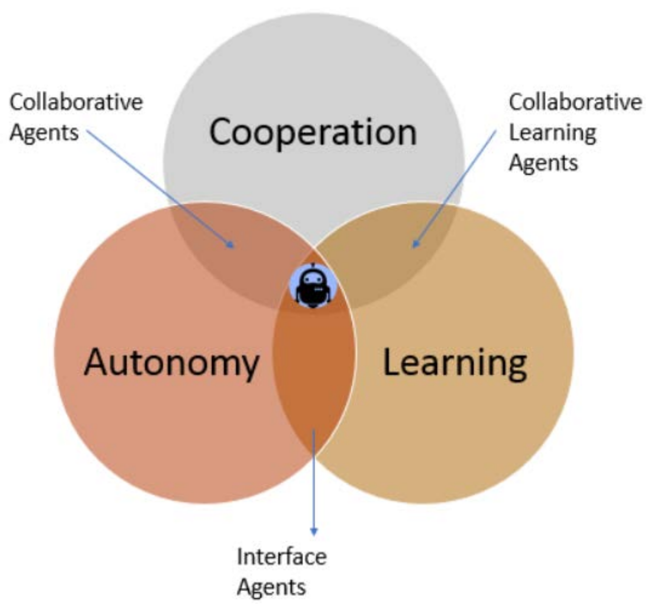

Figure 1: Collaborative learning mechanism for agents

There are several existing Multi agent toolkits available in the market, both open source and proprietary. We discuss below some of the features which are leveraged by Collaborative Cognition (CC) platform, these include

- Compatibility: Different Multi-Agent platforms often lock down agents and their metadata to a specific ecosystem. This includes specific devices (Computer, Mobile etc.), operating system (Windows), Simulation Toolkits, specific communication technologies etc. There have been several attempts in coming up with generic toolkits and interoperable guidelines which can create agents that are compatible across devices, problem domains etc. Some of the notable include, JADE (FIPA guidelines), MadKit etc.

- Agent creation: All the major toolkits like JADE, Anylogic, MadKit, provide for a lifecycle management module for Agents. This include creation of agents, providing programmable constructs for defining agents states, transitioning between agent states which could be passed on a timer, condition, a communication received (message) etc. Finally, when should an Agent (agent class) should be disposed of. All these functionalities are often abstracted in a module named ”Agent Container”.

- Agent Manager: Toolkits in addition to the creation of agents additionally provide with functionalities like Agent Naming, registration of agents which may have been created outside, communication between agents etc. in addition to above discussed. This falls under Agent Management functionality. Different toolkits provide different mechanisms for achieving this, for example, Anylogic provides programmatic interfaces to get a list of registered agents, their states etc., while JADE provides an independent module named Remote Management Agent (RMA) for this.

- Agent population: Agent Population is an important concept in the field of Agent simulations. Often there is a need to create thousands of agents of similar nature. As an example consider a scenario of a bank, where a programmer may attempt to find an optimal number of service executives. To do so one would need to mimic a customer walking in the branch, interacting with service executives for a couple of minutes and then leaving. Toolkits provide for higher level constructs for creating agent population directly to save on development effort. Toolkits further allow for constructs used to include randomness in Agent Population, to extend above example, with some probability (or rule) a customer agent may interact with service executive for 2 minutes, while another one can interact for 5 minutes

- Agent communication: Agent communication is an important aspect for Multi-Agent systems. Each of the platforms and toolkits support agent communication, but the mode of this communication can differ and have a direct impact on a functionality of the application. Several modes of communication include Local, Network, Blackboard etc. A new and upcoming communication protocol includes Blockchain, which ensures reliability, security, and traceability of messages passed among participating agents.

Comparison of some of the popular Multi Agent Platforms is presented in Figure 2

3. Model description

3.1 Overview

The main goal of this work was to model the price of a product P leveraging collaborative decision-making approach. Procurement of the product P is done in the marketplace and usually, procurement strategy is solely based on the understanding of the procurement specialist. At the time of procurement, the procurement specialist comes up with a finger pointing prediction for the price of product P. But, due to the short-sightedness of the procurement specialist in guessing the product price, this may lead to a wrong procurement strategy impacting organization's profitability. In this work, we used statistical models to

Name	Language	License	Communication	Compatibility
Altreva Adaptive Modeler	Genetic Programming	Proprietary	No	No
Agent Builder	JAVA (KQML)	Proprietary	Yes, Supports Inter Agent Communication. (via Agency Manager)	No
AnyLogic	JAVA	Proprietary	Yes, Support Agent Communication (via Message Passing)	No
Cormos	SmallTalk and VisualWorks	OpenSource	Yes	No
ABLE	JAVA (Beans)	IBM Alphaworks	Yes	No
JADE	JAVA	OpenSource	Yes	FIPA Guidelines
REPAST	JAVA	OpenSource	Yes	No
SWARM	Object C/JAVA	OpenSource	Yes	No
NETLOGO	Logo Dialect/JVM	OpenSource	Yes	No
IBM Aglets	JAVA (Mobile Platform)	OpenSource	Yes	No

Figure 2: Comaprison of multiagent platforms

predict the price of the product using historical data. We also propose three predictions of the prices from the perspective of three different agents. (i) A machine learning based agent, (ii) FeedStock based agent(i.e. the products which are used for creating the product P) and (iii). Econometric agent leveraging econometric models to predict the price of product P from the perspective of market dynamics using supply and demand volumes of the product in the market. In this work these agents are autonomous software entities or human domain experts.

3.2 Need for three different agents

The prices of products can be very volatile. The volatility of prices depends on many factors such as supply amount, demand amount of the product, the prices of the materials which are used to create the product and also in this particular case it was found that the price of the product P is also dependent on the prevailing oil prices in the market. Also, instead of coming up with one single global model with all these features, it can be advantageous if multiple predictions are produced using different modelling procedures and then all these predictions could be aggregated together to come up with one single finger pointing prediction. The advantage of having three different agents is, when the prediction produced by all three agents are close enough, this leads to higher confidence about the consistency of the predicted price. On the other hand, since machine learning (ML) based agent or the feedstock(FS) based agent does not consider the perspective obtained from the market dynamics, their predictions are never affected by market dynamics. So, with new information, the econometric agent sometimes may produce better price predictions as compared to other two agents and vice versa. This is advantageous in coming up with one single prediction since different perceptions of agents are taken into account while producing the prediction for the product P.

3.3 Formulation of models

Prediction of price for product P is done for a time interval T_1 to T_n. The features that were used for predicting the price of the product P, are prices of four feedstocks which in this paper will be denoted by FS_1, FS_2, FS_3, FS_4. It is to be noted that feedstocks are the products which are used for preparing the product P. Additionally, crude oil prices which will be denoted by CO are also used. This prediction problem is addressed as an online prediction problem. During the time period T_1 to T_n, we considered the data from the i^{th} month (which is denoted by M_i) as the training data and based on that the predicted price for the commodity is produced for $(i+1)^{th}$ month. In the time interval of $(i+1)^{th}$ month, the predictions are generated on a weekly basis for all weeks in that month. We will denote the weeks of $(i+1)^{th}$ month as $W_{(i+1),1}$, $W_{(i+1),2}$,...$W_{(i+1),k}$ where k can be 4 or 5. Similarly, the weeks for the month i will be denoted by $W_{i,1}$, $W_{i,2}$,...$W_{i,l}$ where l can be 4 or 5. This terminology will be kept consistent for all the individual models throughout the paper. This methodology for prediction produced promising results in contrast to state of the art Time Series models. Hence, the modelling approach, that considers the actual prices for the month M_i as the training data and then predicts the prices for the month M_{i+1} worked out reasonably well. Perhaps the reason could be the volatile nature of the prices and thus long term history may not be much useful for predictions. In the next few subsections, we present a detailed overview of each of the models pertaining to individual agents.

3.4 Agent 1: Machine Learning Agent

The machine learning agent produces online predictions. Consider, M_i as the training period and the weeks in M_i are $W_{i,1}$, $W_{i,2}$,...$W_{i,l}$. We consider the following model:

$$P_{i,j} = \alpha + \beta_1 FS_{1_{i,j}} + \beta_2 FS_{2_{i,j}} + \beta_3 FS_{3_{i,j}} + \beta_4 FS_{4_{i,j}} + \beta_5 CO_{i,j} + \epsilon_{ij} \text{ for } j \in \{1, 2, .., l\}$$

where,
$P_{i,j}$ = Price of the product P in the j^{th} week of the i^{th} month,
$FS_{1_{i,j}}$ = Price of FS_1 in the j^{th} week of the i^{th} month,
$FS_{2_{i,j}}$ = Price of FS_2 in the j^{th} week of the i^{th} month,
$FS_{3_{i,j}}$ = Price of FS_3 in the j^{th} week of the i^{th} month,
$FS_{4_{i,j}}$ = Price of FS_4 in the j^{th} week of the i^{th} month,
$CO_{i,j}$ = Price of crude oil in the j^{th} week of the i^{th} month,
ϵ_{ij} are Gaussian i.i.d. random variables.

In the above regression models, α, β_1, β_2, β_3 and β_4 are the coefficients which are estimated based on the actual prices of the target and input variables for M_i. The estimated coefficients are used for predicting the price of the target variable P, for every week for month M_{i+1}.

It is to be noted, the prices for the input variables FS_1, FS_2, FS_3, FS_4 and CO are to be estimated for the M_{i+1} as the model will not have the actual values of the input variable for month M_{i+1}. Hence, the estimated price of the input variable for every week in M_{i+1} is calculated in the following way

$$H_{(i+1),j} = [H_{(i+1),j-1} + \Delta_{ij} + \frac{\sum_{j=2}^{l} \Delta_{ij}}{l-1}] I(j \geq 2) + H_{i,\max\{4,5\}} I(j = 1)$$

where,
$H \in \{FS_1, FS_2, FS_3, FS_4, CO\}$
I is the indicator function
$\Delta_{ij} = H_{i,j} - H_{i,j-1}$ where $j \in \{2, 3, ..., l\}$

Estimated values of the input variables for month M_{i+1} is used for predicting the price for the product P for month M_{i+1}.

3.5 Agent 2: feedstock based Agent

The feedstock based agent also, produces online predictions. Consider, M_i as the training period and the weeks in M_i are $W_{i,1}$, $W_{i,2}$,...$W_{i,l}$ corresponds to input data. We consider the following model:

$$P_{i,j} = \alpha + \beta_1\widehat{FS}_{1_{i,j}} + \beta_2\widehat{FS}_{2_{i,j}} + \beta_3\widehat{FS}_{3_{i,j}} + \beta_4\widehat{FS}_{4_{i,j}} + \epsilon_{i,j} \text{ for } j \in \{1, 2, .., l\}$$

where where,
$P_{i,j}$ = Price of the product P in the j^{th} week of the i^{th} month,
$\widehat{FS}_{1_{i,j}} = \frac{\sum_{j=1}^{\max\{4,5\}} FS_{1_{i-1,j}}}{k}$
$\widehat{FS}_{2_{i,j}} = \frac{\sum_{j=1}^{\max\{4,5\}} FS_{2_{i-1,j}}}{k}$
$\widehat{FS}_{3_{i,j}} = \frac{\sum_{j=1}^{\max\{4,5\}} FS_{3_{i-1,j}}}{k}$
$\widehat{FS}_{4_{i,j}} = \frac{\sum_{j=1}^{\max\{4,5\}} FS_{4_{i-1,j}}}{k}$
ϵ_{ij} are Gaussian i.i.d. random variables.
Once the estimated values of the coefficients α, β_1, β_2, β_3 and β_4 are obtained, the predicted prices for the product P in the month M_{i+1} is calculated as

$$\widehat{P}_{(i+1),j} = \widehat{\alpha} + \widehat{\beta_1}\widehat{FS}_{1_{(i+1),j}} + \widehat{\beta_2}\widehat{FS}_{2_{(i+1),j}} + \widehat{\beta_3}\widehat{FS}_{3_{(i+1),j}} + \widehat{\beta_4}\widehat{FS}_{4_{(i+1),j}} \text{ for } j \in \{1, 2, .., k\}$$

where,
$\widehat{FS}_{m_{(i+1),j}} = \frac{\sum_{j=1}^{l} FS_{m_{i,j}}}{l}$ for $j \in \{1, 2, ..., l\}$ and $m \in \{1, 2, 3, 4\}$

3.6 Agent 3: Econometric Modelling Agent

Product P is a supply constrained product. Hence, demand amount always surpasses supply amount. Hence, an assumption was made that the price of the product is solely affected by the supply volumes. Hence we consider the supply volumes for predicting the prices of the product P. Initially, we split the time horizon T_1 to T_n in two sections as $[T_1, T_{train}]$ and $[T_{train+1}, T_n]$ where the data from $[T_1, T_{train}]$ is used for training the model and $[T_{train+1}, T_n]$ is the prediction period. Also, due to scarcity of data for supply volumes in the time period $[T_{train+1}, T_n]$ the supply volumes are also to be estimated for prediction period. During the training phase, modelling of the prices was done considering supply volume as the input variable. The model is

$$P_t = \alpha + \beta_0 S_t + \beta_1 S_t^2 where, 1 \leq t \leq T_{train}$$

where, P_t = Price of product P at the time point t and,
S_t = Supply volume of product P at the time point t
The equation above can also be represented as,

Price of product P = f(*Supply volume*)

We denote the estimated modelling function by $\hat{f}$. Now, consider the month M_i for which the price of product P is known and the price for product P is to be predicted for month M_{i+1}. For this, we first estimate the supply volumes of the product P for every week $W_{i,j}$ in month M_i using the equation

$$\widehat{S}_{i,j} = \hat{f}^{-1}(P_{i,j}) \text{ for } j \in 1, 2, ..., l$$

where, $\widehat{S}_{i,j}$ denotes the estimated supply volume for j^{th} week in the i^{th} month and $P_{i,j}$ denotes the actual price of product P for j^{th} week in the i^{th} month. In the next step, we calculate the estimated volumes $\widehat{S}_{(i+1),j}$ for every week in month M_{i+1} using the equation

$$\widehat{S}_{(i+1),j} = [\widehat{S}_{(i+1),j-1} + \Delta_{ij} + \frac{\sum_{j=2}^{l} \Delta_{ij}}{l-1}]I(j \geq 2) + \widehat{S}_{i,\max\{4,5\}}I(j = 1) \text{ for } j \in \{1, 2, ..., l\}$$

where,
I is the indicator function
$\Delta_{ij} = \widehat{S}_{i,j} - \widehat{S}_{i,j-1}$ where $j \in 2, 3, ..., l$
Once we have ontained $\widehat{S}_{(i+1),j}$ for every week in month M_{i+1}, we caluclate the predicted price of the product P for the same period using the equation

$$\hat{P}_{(i+1),j} = \hat{f}(\widehat{S}_{(i+1),j}) \text{ for } j \in \{1, 2, ..., k\}.$$

3.7 Aggregating the predictions from different agents

Using individual models agents produce predictions for product P in every week of a specific month. Now, these predictions are aggregated through a cognitive collaboration among agents to reach a single finger pointing prediction. In this case, to produce that single finger pointing predicition the agents are allowed to get into a collaborative game. The game goes on for certain number of rounds. In the initial round the agents propose the raw individual predictions that are obtained from the models. At the end of the initial round, each agent updates his/her prediction and proposes the updated predictions for the 2^{nd} round. Then, again they refine their predictions at the end of 2^{nd} round. They keep on proposing these predictions in a cyclic manner until they reach a stopping criterion. The mathemtical formulation for the collaborative decision making process can be represented in the following way. Consider for time point t in round r agent i proposed the prediction to be $\hat{p}_{i,t}^{r}$. Then the updated prediction for round $(r + 1)$ for agent i is given by

$$p_{i,t}^{r+1} = \frac{p_{i,t}^{0} + \sum_{k=1}^{3} w_{k,t} p_{k,t}^{r}}{\sum_{k=1}^{3} w_{k,t}} \text{ where, } i = \{1, 2, 3\}$$

and $p_{i,t}^{0}$ is the initial prediction of agent i at time t and $w_{i,t}$ = root mean squared error of final collaborative prediction for agent i till time $(t - 1)$. The stopping criterion for the collaborative iteration is

$$|p_{i,t}^{r+1} - p_{i,t}^{r}| < \epsilon \text{ where } \epsilon \text{ is a pre-specified threshold for } \forall i.$$

Once the stopping criterion is met the final three predictions are aggregated to produce one single finger pointing prediction using the following formulation:

$$p_t^{Final} = \frac{\sum_{i=1}^{k} w_{i,t} p_{i,t}^{R_0}}{\sum_{i=1}^{k} w_{i,t}} \text{ where } R_0 \text{ denotes the converging round.}$$

3.8 Formulation of the confidence band

We compute confidence band $100\alpha\%$ for the final prediction p_T^{Final} obtained at time point $T \in [T_{train+1}, T_n]$ using the following formulation:

$$[p_T^{Final} - \frac{s_T t_{1-\frac{\alpha}{2},v-1}}{\sqrt{v}}, p_T^{Final} + \frac{s_T t_{1-\frac{\alpha}{2},v-1}}{\sqrt{v}}]$$

where, $s_T = \sqrt{\frac{s_{1,T}+s_{2,T}+s_{3,T}}{3}}$
$t_{1-\frac{\alpha}{2},v-1}$ = t distribution value for $1 - \frac{\alpha}{2}$ with $v - 1$ degrees of freedom
and

$s_{i,T}$ = root mean squared error of i^{th} agent's individual converged prediction for the time interval $T-v+1$ to T where v is a pre-specified positive integer.

4. Results

In Figure 3 we present the actual prices of product P and the initial predicted prices of P obtained by each agent. It can be seen that the prediction from each of the agents is close enough to the actual values.

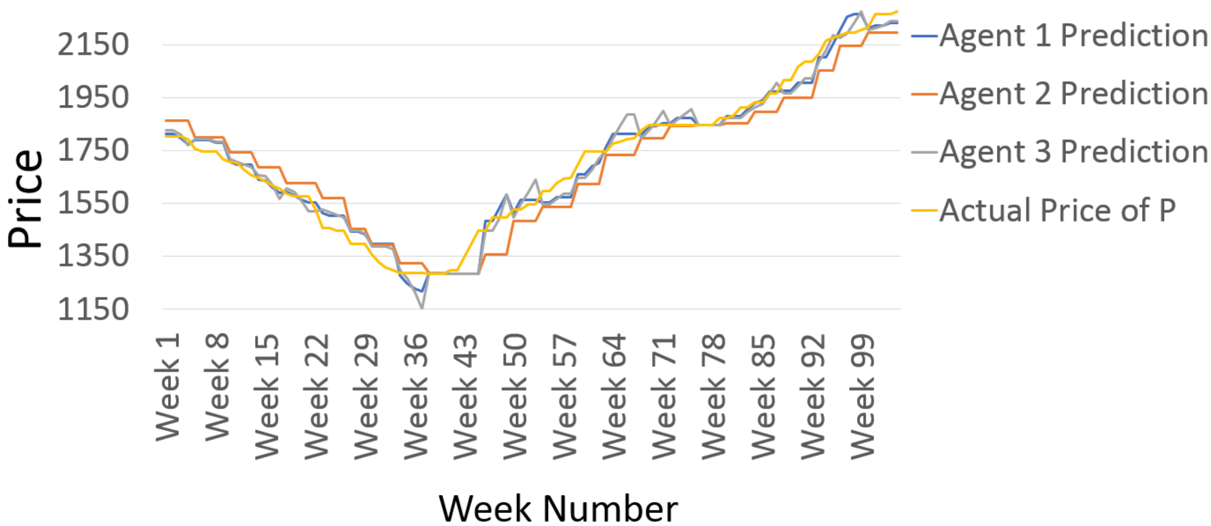

Figure 3: Prediction from Agents and Actual Price of P

Root mean squared error (RMSE) and Mean absolute percentage error (MAPE) for each agent's raw prediction is given in Table 1. The formula for RMSE and MAPE are

Agent	RMSE	MAPE
Agent 1	44.46	2.07
Agent 2	72.73	3.72
Agent 3	49.23	2.35

Table 1: Accuracy of prediction

given by:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\text{predicted price at time t - actual price at time t})^2}$$

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{|\text{predicted price at time t - actual price price at time t}|}{\text{actual price in time t}}\text{X100}$$

Also, in Figure 4 we plot the Absolute Percentage Error(APE) of predicted price obtained by each agent. The metric for APE is given by

$$\text{APE of prediction at time } t = \frac{|\text{predicted price at time t - actual price price at time t}|}{\text{actual price in time t}}\text{X100}$$

It can be seen that the ML-based prediction has consistently produced better results as compared to other two methodologies We also present a 95% confidence band along with the point prediction for product P generated through collaborative decision-making procedures by the agents. In Figure 5 the point predictions are given for each week along with the lower and higher confidence bands. RMSE of the point predictions displayed in Figure 5 is 41.099.

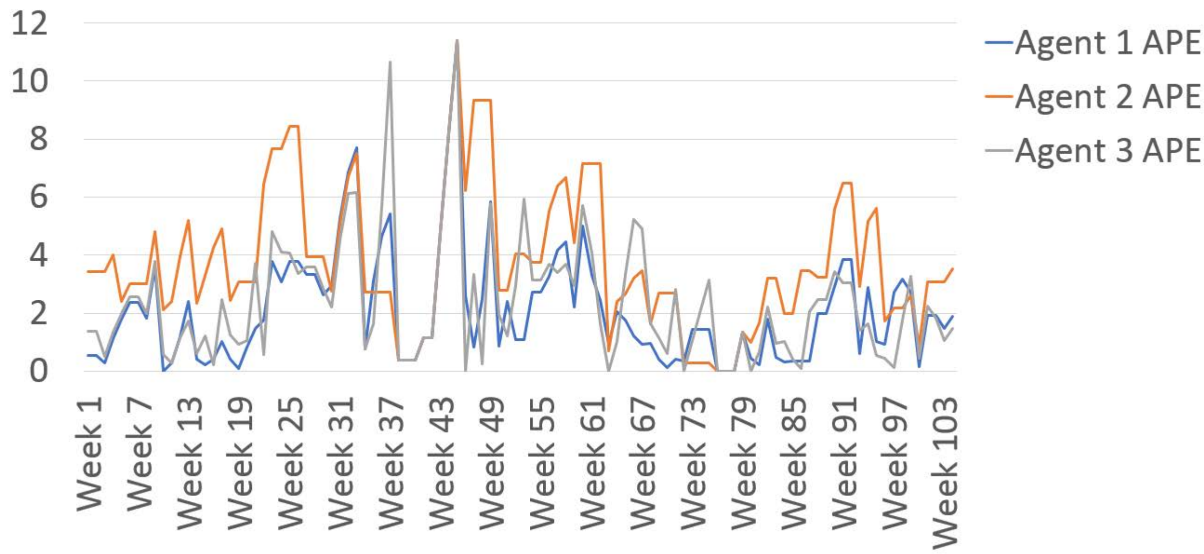

Figure 4: APE of the predictions from Agents

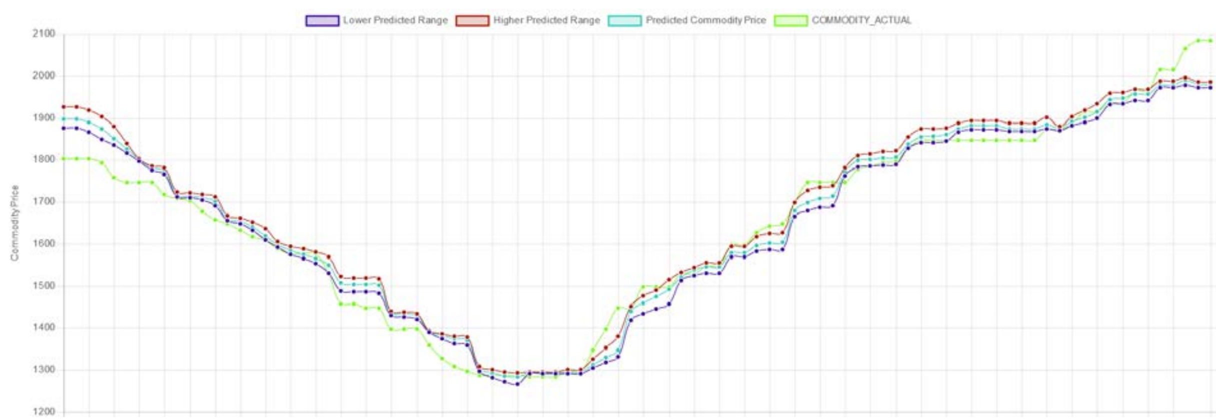

Figure 5: Predictions through CDM and 95% confidence band

5. Collaborative Cognition (CC) Platform

5.1 Why a Collaborative Cognition (CC) platform is needed ?

Price prediction of a commodity includes the study of complex market forces which can have a direct or indirect impact on pricing of this commodity. Typically these market forces are studied by different experts. These expert's make commodity price predictions based on signals from the specific domains.

Economic forces: A suppliers market (where supply is less than demand) would see prices going up at linear intervals, since higher pricing may not be a deterrent for a demand of the commodity. On another hand in a buyers market (demand is less than supply) demand would be extremely sensitive to the price of the commodity, we can expect prices to remain stable or even fall due to supplier competition. Commodities which are cyclic in nature may move between these two market types based on seasonal production, festive demands etc. An Economist studies these forces and attempts to predict the fair future commodity value.

Production forces: Manufacturing of commodities often requires other raw materials and base commodities (Feedstocks). Very often these feedstock's form a considerable portion of manufacturing cost and thus have a direct bearing on the pricing of the commodity being manufactured. Very often, big (major) manufacturers can come together and control the total commodity supply in the market (eg: OPEC) in an attempt to check the falling commodity prices. A Raw Material specialist would be doing a market survey to understand the current ecosystem and would be basing his price predictions based on it.

Supply Chain: Events in the supply chain can potentially have a huge impact both on commodity prices and commodity availability. Consumers of commodities keep a regular check on these events, to gauge future supply of the commodity and changing patterns. For example, a news of unplanned factory shut down, in a suppliers market, would cause consumers to start buying in bigger than normal quantities for meeting future requirements, causing prices of the commodity to rise. Similarly, a news of capacity expansion in a manufacturing unit may cause prices to dip. Supplier Relations (Supply Manager) role is to keep regular checks on various existing suppliers and upcoming suppliers and recommend prices which are not only low but also ensures good relations and continuous supply for an organization.

Macro Economic: Other macroeconomic factors like Geo-Political relations, Inflation and Interest rates, regional regulations (Minimum Support Price) etc. may also influence commodity prices, as these are considered to be good indicators of future growth (or decline). A Macro Economist (Trade Regulator) would be studying all regional and international regulations and economic conditions to predict commodity prices. A pictorial representation of different market forces as for example that affect the price of commodities is given in Figure 6.

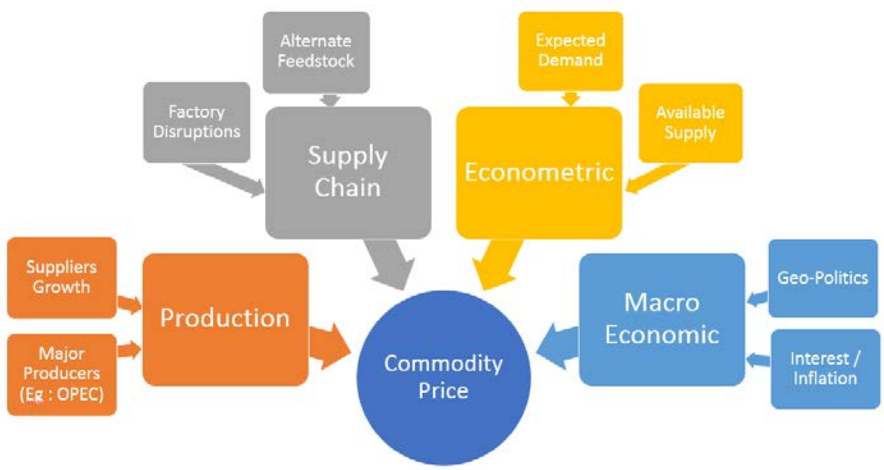

Figure 6: Different components that affect price of commodities

Once the experts have made their recommendations, it is left to Procurement Head to collate all of these recommendations and formulate a short term and long term procurement strategy. As one can appreciate this is a non-trivial task and often decrypting predictions to prevailing market conditions in specific domains is nearly impossible. Given the one time nature of communication among domain experts and leaving the final calculation of commodity price prediction to one individual, there is a very high chance for errors in the procurement process, since at no time any of the experts is aware of holistic positioning of market forces. At no time in the process, any of the experts or procurement head gets the full picture of the market on which more accurate procurement strategy could be formulated. This is the problem Collaborative Cognition platform attempts to resolve. Collaborative Cognition platform allows all cooperating autonomous prediction agents, representing

dynamic market forces as described above, to collaborate among themselves, and over iterations reach to a consensus around commodity prices. For example, A agent specializing in pricing based on feedstock would revise his prediction if he gets to know of prediction from EM Model indicating factory disruptions etc.
A pictorial representation of the price prediction dynamics through CC platform is given in Figure 7.

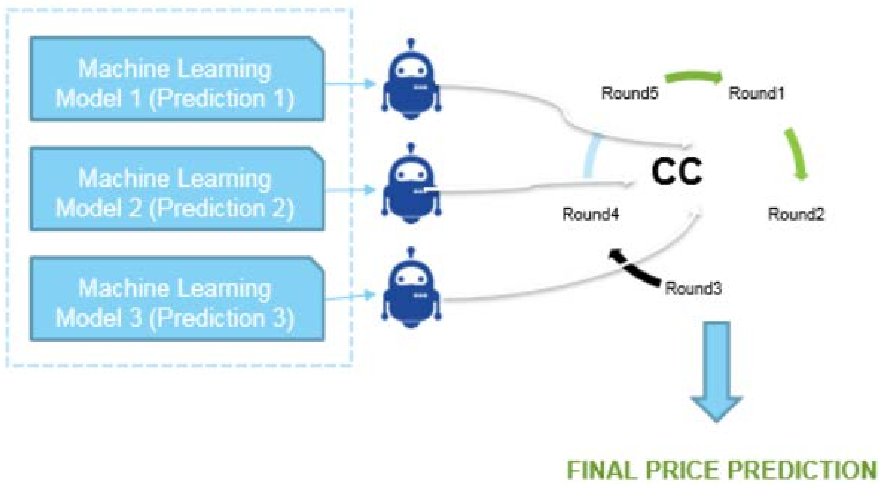

Figure 7: Dynamics of Price Prediction through Collaborative Cognition (CC) platform

5.2 High level design of Collaborative Cognition (CC) platform

Platform is designed to allow for different kinds of games and agents to co-exist. These games could be cooperative, where agents are working together towards achieving a single goal via collaboration, information (feature) exchange etc, like in the price prediction game above where all agents collectively attempt to make the best prediction or could be competetive where every agent tries to outperform other existing agents, for example in a bidding setup.

Platform also allows for different types of agents to exist, they could be software impersonation of domain experts, or real human experts themselves. One of the agents could act as the orchestrator of the game, responsible to set up the game, invite participants, and leveraging game theory principles iteratively converge them to singular price prediction. Platform lets agents collaborate with each other via message passing (REST API's). An agent can either send a directed message to game orchestrator to submit initial predictions, fetch predictions of other agents, submit updated predictions, get game status etc. or to any other participating agent inviting for feature exchange. A pictorial representation of the structure of the platform is given in Figure 8.

Once the convergence is reached, Platform lets all the data then exposed via web (REST) APIs, to enable a dashboard for human (Procurement specialist) where they can either choose to the final predictions, initial beliefs from participating agents, confidence bands, and round by round interactions among agents. A pictorial representation of one instance of a game in CC platform is given in Figure 9.

Platform, although initially designed for addressing price prediction problems, can be leveraged in various domains needing collaborative decision making, that is, where diverse stakeholders need to converge towards collective decisions. Some of the domains apart from commodity prediction include collaborative hiring, collaborative risk classification,

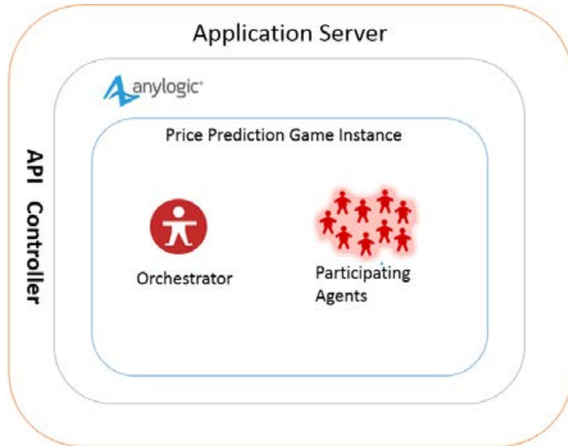

Figure 8: High Level Structure

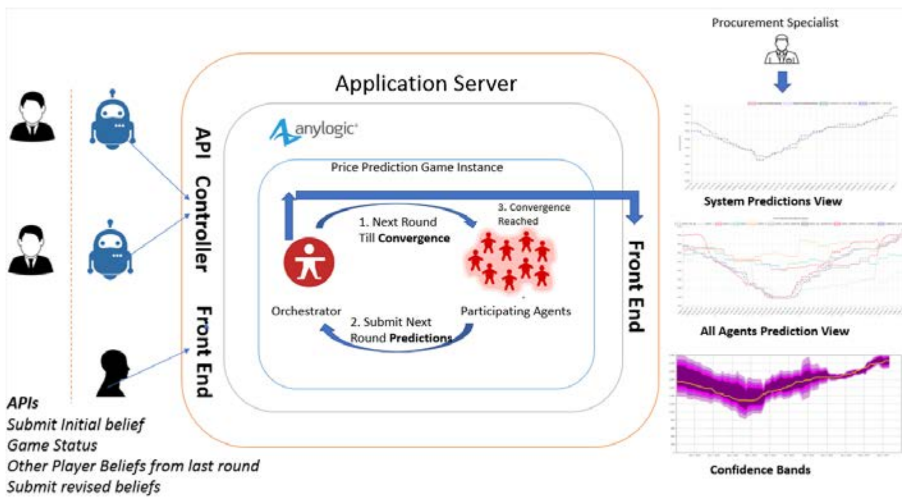

Figure 9: Detailed description of the platform

supplier management and negotiations, collaborative paper appraisal and selection, Banking domain early warning systems etc.

6. Conclusion

In this paper, we proposed collaborative decision making (CDM) among agents for predicting the price of a commodity leveraging Collaborative Cognition (CC) platform. To begin with, each agent proposed a prediction of prices and then agents took part in a collaborative game through a collaborative cognition (CC) platform to come up with an aggregated prediction. It was found that root mean squared error (RMSE) of predictions from individual agents are already small. Among the three agents, agent 1 was found to produce predictions with an RMSE of 44.46. This agent used individual feedstock prices and also crude oil prices to produce the prediction of the product P. RMSE of the predictions from agent 3 which used a supply-driven modelling technique is 49.23. Also, while modelling, this agent used a very small amount of historical data. The prediction would have been more accurate if the historical data size was substantially large. Agent 2 which modelled the price of the product only leveraging feedstock prices produced predictions with RMSE 72.73. Once the agents took part in a collaborative decision-making process, the aggregated prediction from

CDM has RMSE 41.099 which is better than that obtained by individual agents. Hence, collaborative decision making helped agents to come up with a more accurate prediction.

In some cases, the collaboration might lead to predictions which may not be as accurate as individual predictions. But, the advantage of this modelling approach is, even when agents produce individual predictions from a diverse perspective of the observed environment or data, once they collaborate with each other, their prediction accuracy increased which in turn leads to a reasonably accurate aggregated prediction. Also, even when if one of the agents produce predictions which are off by a large margin from the actual price and this may happen due to scarcity of feature from data, once the agent takes part in a collaborative decision making with other agents who had a diverse feature setfa and had a better prediction, the particular agent's prediction also becomes better in the process. The effectiveness of CDM method is found to be advantageous in producing accurate predictions.

7. Future Work

The work presented in this paper can be extended in various directions. We discuss below two major extensions of the current work.

Feature Exchange: A cooperating game setup is the one where multiple agents collaborate towards achieving a common goal, example predicting price of a commodity etc. Often such agents, in exchange of an incentive may be willing to share either all or the non critical data sources with other agents in system. By non critical features we mean features which are not central to existance of the agent. This helps all agents to improve their predictions, eventually leading to better system predictions. Developed system currently allows for a primitive form of feature exchange via actual data exchange. This helps agents evolve inorganically and possibly discover information which can be leveraged in their models for predicting commodity prices. We can extend this paradigm by inclusion of a knowledge market place, where insights can be traded among agents for a incentive. To evaluate the usefulness of new information and come up with right pricing strategies, agents can share historical insights or a suitable subset, enabling the consuming agent to measure the usefulness of the new feature. The marketplace can support trading of different categories of features, raw(cheaper) or derived insights(expensive). Insight are typically desired by both consuming and sharing agent, since it brings down time required by consuming agent and also enable data privacy.

Cognitive agent - In the current system, agents update their preferences following a pre-specified methodology. Additionally, in competing game setups, it would be extremely useful for a participating agent to understand strategy being used by other agents before making their move. Regardless of the setup competing or cooperating it would help if agents can delegate strategy making decisions to cognitive impersonations. Agents in MAS can pass information like other participating agents, past iterations and game setups to cognitive impersonation like ACTR, SOAR.

REFERENCES

Richard C., Bermudez Jose Carlos M., Honeine P. (2009), "Online prediction of time series data with kernels", in *IEEE Transaction on Signal Processing*, Volume 57, Issue 3.

Wang W., Men C., Lu W. (2008), "Online prediction model based on support vector machine", in *Neurocomputing*, Colume 71, Issue 4-6.

Dekel O., Gilad-Bachrach R., Shamir O., Xiao L. (2012), "Optimal distributed online prediction using mini-batches", in *Journal of Machine Learning Research*, Volume 13, Issue 1.

Raftery A.E., Karny M., Ettler P. (2010), "Online prediction under model uncertainty via dynamic model averaging: Application to a cold rolling mill", in *Technometric*, Volume 52, Issue 1.

Ghani R. (2005), “Price prediction and insurance for online auctions”, in *Proceedings of eleventh ACM SIGKDD, Internation Conference on Knowledge discovery in data mining*.

Just R.E., Rausser G. C. (1981), “Commodity price forecasting with large-scale econometric models and their future market”, in *American Journal of Agricultural Economics*, Volume 63, Issue 2.

Ferraro D., Rogoff K., Rossi B. (2015), “Can oil prices forecast exchange rates? An empirical analysis of the relationship between commodity prices and exchange rates”, in *Journal of International Money and Finance*, Volume 54.

Borensztein E., Reinhart M. C. (1994), “The Macroeconomic Determinants of Commodity Price”, in *International Monetary Fund*, Volume 41, No.2.

Gargano A., Timmermann A. (2014), “Forecasting commodity price indexes using macroeconomic and financial predictors”, in *International Journal of Forecasting*, Volume 30, Issue 3.

Giannakis M., Louis M. (2011), “A multi-agent based framework for supply chain risk management”, in *Journal of Purchasing and Supply Management*, Volume 17, Issue 1.

Labarthe O., Espinasse B., Ferrarini A., Montreuil B (2007),, “Toward a methodological framework for agent-based modelling and simulation of supply chains in a mass customization context”, in *Simulation Modelling Practice and Theory*, Volume 15, Issue 2.

Jaio J., You X., Kumar A. (2006), “An agent-based framework for collaborative negotiation in the global manufacturing supply chain network”, in *Robotics and Computer-Integrated Manufacturing*, Volume 22, Issue 3.

Javidi, S., Pedzsiz M., Goh S. L., Mandic D.P. (2008), “The augmented complex least square algorithm with application to afdaptive prediction problems 1”, Citeseer.

Nwana, H. S., “Software Agents: An Overview”, in *Knowledge Engineering Review, Volume 11, No. 3.*

Foner L., (1993), “What’s an agent, anyway? A sociological case study, in Agents Memo.

Foner L., (1996), “A multi-agent referral system for MatchMaking”, in Proceedings the First International Conference on the Practical Application of Intelligent Agents and Multi-Agent Technology (PAAM).

Anderson J.R., Matessa M., Lebiere C., (1997), “ACT-R: a theory of higher level cognition and its relation to visual attention”, in Human Computer Interaction, Volume 12, Issue 4.

Laird J. E., Newell A., Rosenbloom P.S. (1987), “SOAR: An architecture for general intelligence”, in Artificial Intelligence, Volume 33, Issue 1.

Requile-Romanczuk A., Mingins C., Yap B., Constant O. (2003), “LEOPARD: a .net based agent architecture”, in AAMAS ’03 Proceedings of the second international joint conference on Autonomous agents and multiagent systems.

Gutknecht O., Ferber J. (2000) “MadKit: a generic multi-agent platform”, in AGENTS ’00 Proceedings of the fourth international conference on Autonomous agents.

Bellifemine F., Poggi A., Rimassa G. (2001), “JADE: a FIPA2000 compliant agent development environment”, in AGENTS ’01 Proceedings of the fifth international conference on Autonomous agents.

Kravari K., Bassiliades N., (2015), “A Survey of Agent Platforms ”, in Journal of Artificial Societies and Social Simulation.