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A Multi-Agent based simulator for strategic bidding in day-ahead energy market

Pooja Jain [a], Akash Saxena [b]

[a] Department of Electrical Engineering, Swami Keshvananad Institute of Engineering & Technology, Management & Gramothan, Jaipur, 302025, Rajasthan, India

[b] School of Computing Science and Engineering (SCSE), VIT Bhopal University, Bhopal-Indore Highway, Kothrikalan, Sehore, Madhya Pradesh, 466114, India

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Abstract

Countries all around the globe are continuing to restructure their energy markets in various ways. To deal with electricity market challenges, a flexible simulation platform is very important to maintain synchronization between market structure, market players and their behavior. So, for this purpose, in this paper, a new simulation tool based on Multi-Agent System (MAS) is proposed which not only helps us in evaluating existing market regulations but also aids in exploring and testing novel market designs before their implementation. This proposed system works in three phases of estimation, control & action with real-time monitoring. To test the applicability of the proposed MAS-EMTS, the framework is implied in two test cases of Power System. The investigations demonstrate the adaptability of the proposed MAS-EMTS based electricity market trading simulator(MAS-EMTS) which empowers the agents to give profitable bids, and modified generator cost characteristics with maximum profit.

Keywords

Agent; Multi-agent system(MAS); Principal component analysis(PCA)

Nomenclature

MUT_m
: Minimal start time of GENCO of mth block

MDT_m
: Minimal shut down time of GENCO of mth block

$\alpha_m^{on}(t)$
: Time for mth block of GENCO has been constantly 'ON' at the mth hour end

$\alpha_m^{off}(t)$
: Time for mth block of GENCO has been constantly 'OFF' at the mth hour end

M
: Existing number of Opponents

T_{off}
: GENCO OFF hours at the instant of start

C_h
: Expenditure on Hot Start-UP of GENCO

C_c
: Expenditure on Cold Start-UP of GENCO

T_c
: Fixed Cooling time

$C_m(t)$
: Operating Expenses for mth block of GENCO

C_m^u
: Start UP cost (Nonlinear exponential)

C_m^d
: Incessant shut down expenditure

q_m^M
: Bid cost for mth block for Mth Competitor

$C^{p}_{\underline{m}}(t)$
Production cost (Non differentiable, non-convex function)

P_m
Higher limit of GENCO output of $k\text{th}$ block

$\underline{P}_{\underline{m}}$
Lower limit of GENCO of $m\text{th}$ block

$\chi_m(t)$
Bit field

a,b & c
Cost defining constants

d,e
Loading effect of valve point constants

1. Introduction

Each region had its own electric utility that would provide generation, transmission, and distribution of electricity. Under rate-of-return regulation, the utility would recommend investments to regulators and, if approved, the costs would be included in the rate base.

In a power pool, several neighboring utilities are connected via the transmission network, allowing the trade of energy across regions. Trade has both cost and reliability benefits — drawing from a larger fleet of generators means that the required energy can be supplied at a lower cost. The wholesale market allows real-time trade and pricing of energy. Most markets began as single-price markets, where transmission constraints were ignored for purposes of pricing.

To satisfy constraints, some out-of-merit generation is asked to produce, displacing some in-Merit generation. This approach only works well if there is sufficient transmission so that constraints rarely bind. Transmission is critical in that it is a transmission that enables the wholesale market. Efficient new transmission lines often eliminate the congestion rents that would otherwise motivate the investment. Forward-looking congestion rents are an inadequate means of cost recovery for lumpy transmission investments. Cost recovery is possible through additional charges, but transmission planning and investment occur as part of the regulatory process. Managing the relationship between transmission investment and generation investment is a problem that must be handled. Long-term transmission plans must be understood to make the best generation investments, but the generation investments ultimately affect the transmission plans.

The shift to nodal markets is just one of many enhancements to current markets. Market rules are constantly being improved to address observed flaws and to respond to new challenges. Good governance is essential for the markets to see steady improvement. The cornerstone of a restructured electricity market is the wholesale market in which generators compete to serve load. Most retail customers are poor electricity shoppers, requiring education and objective information to identify the best contract[1], [2].

One might think competition would be intense because the price is the salient attribute of the retail service. But most customers have a strong preference to minimize cost, and so are less able to shop around for the best deal. The coming smart home will enable both the shifting and reduction of demand for the benefit of customers.

The retail competition will become increasingly important as smart home technologies are developed and adopted. Innovative service providers that do the best job of maximizing customer value will prosper, according to the World Energy Agency (WEA). This coordination issue lacks a clear solution. Distribution, or the low-voltage wires that deliver power to our homes and businesses, is the last component of the market model. In the reconstructed market, the distribution firm continues to be a monopolistic utility. However, even in this area, new distributed generating and storage technologies are being launched, which is changing the scene. With the evolution of restructured power markets, profit-making strategies are adhered to by the generating companies. For utilizing the knowledge of existing market conditions, often power producers employ a Multi-Agent Framework. This framework helps to generate companies to earn more profit. In the restructured power market environment, these systems must be able to handle new requirements, such as the widely diffused nature of the data, the unpredictability of competitors' bid data, and changeable load demand. Multi-Agent systems (MAS) have attributes that meet these prerequisites. A certain degree of distributed or collective intelligence can be accomplished through the connection of these agents with one another, participating or contending to achieve their objectives.

In the same line of order, this paper presents a detailed overview of MAS for solving strategic bidding problems in the day-ahead energy market by adopting a strategy based on agent-based simulation.

Many research articles have advocated agent-based modeling and simulation (ABMS) as a feasible modeling approach for complex, socio-technical problems[3] and qualified as a scientific instrument[4]. Agent-based simulation approaches have been used to analyze power systems and markets in particular and have received a lot of attention[5]. To date, the strong focus of ABMS techniques in the field of electrical systems have been on wholesale electricity markets[6], [7], [8], [9], [10], [11], [12]. As a result, agent models have primarily focused on large generation corporations, which are often thought to operate rationally or at most bounded rational in the sense of having inadequate information[13]. In[14], A cooperative multiagent optimization method (CMAOM) for wind farm power delivery maximization has been proposed. In,[15], MAS application for smart grid protection is analyzed and superiority of MAS over other conventional method is observed. In[16], practical uses of MAS in power systems have been demonstrated. The paper discussed constructional and design aspects of agent formulation for the power system operation tasks. Management and simulation process of power system have been handled by MAS developed in Ref.[17]. In the above-mentioned paper, the authors have explored the power system reliability based on the Monte-Carlo simulation.

In[18] author design Predictive Voltage Hierarchical Controller for Is-landed Microgrids Under Limited Communication using agent-based simulation. In[19] author propose multiagent system-based Distributed Coordinated Control for Radial DC Microgrid considering transmission time delays.

In[20], [21], [22] author proposed various algorithms to solve strategic bidding problem. The energy corporation's producing art is aligned with what can be done in this information-rich world, but the path forward is unclear. What methods should be used to establish new markets? How may data trade be implemented in a flexible way that allows for better decision-making and evolves with change in the business sector and innovative thinking? What may the transformation look like as present systems are gradually replaced by new methodologies? What regulations and plan frameworks should be established to ensure dependable administration and a robust framework for the country's economic security? The analysis must be backed up by simulations to resolve these issues before commencement. Until now, market simulators have been used to recreate the technological aspects of executing the framework[23], [24], [25]. Similarly, a market-based system shifts the control ideal model away from centralized power and toward appropriated, autonomous decision-making[26]. When properly defined, the result would provide greater efficiencies as well as a consistent performance of an operation, and it will also be a framework with a specific type of consistency, a system that continues to operate within specified constraints such as climate, and a framework that requires the use of complex framework hypothesis to discover emergent behavior conduct and direct it in a useful manner. In[27], the author suggested a market model built on agents, with contributions corresponding to both storage and generation power facilities. In contrast to the agents who utilize heuristics and a trial-and-error technique, the suggested model uses multi-step optimization to optimize profit by identifying the bidding curve. In addition, the authors employed a reward adjuster to term financial assets depending on an hourly price forward curve (HPFC), which takes into consideration a participant's market strength.[28] advocated for a multi-layer MAS architecture to investigate market participant behavior. Renewable energy producers and wholesale market actors, who optimize bidding/offering tactics, have been represented in the first layer, while customers, such as Plug-in Hybrid Electric Vehicle (PHEV) owners and Demand Response(DR) program participants, have been modeled as independent agents in the second layer. The basic goal of a responsive consumer is to increase benefit while maintaining well-being. The authors also employed an incomplete information game theory method to model market player interactions in real-time and day-ahead marketplaces.[29] suggested a MAS-game theory-based reverse auction model for a micro-grid market operation that takes renewable and conventional Distributed Energy Resources (DER) into account. The authors used the properties of MAS to monitor, control, and perform a reverse auction process for DERs, and a competitive game-theory reverse auction model was used to plan the DER unit commitment for the 24h of the day using a one-day ahead market strategy. The proposed model was also actually tested on a smart grid test system at Florida International University, and it was discovered that it can be applied in the current electric utility grid as new assets are added to the system.

The agent-based computational method is particularly suited for studying the behaviors of a complex adaptive system, such as an electricity market. Autonomous, proactive, and reactive agents with embedded learning capabilities can accurately mimic the diverse actions of heterogeneous market participants. Based on conducted literature review, the following research objectives are framed for this paper:-

1. To provide an intelligent bidding price simulator which is proposed by deep learning of historical experiences by the means of Rival's bid data and demand anticipation in which maximum uncertainty is present.

2. To provide uncertainty by deep learning methods, the Optimization tool is used to get optimal results to feed the next agent in the system as described in the methodology.

3. To provide profit-making bids which are obtained from Artificial Neural based agent with the help of Optimal bid calculator agent.

4. To provide a Generator Cost coefficient which is also obtained to get maximum profit by reducing generator production cost.

5. To provide profit-making bids and generator cost coefficients; Optimal value of MCP and Maximum Profit are obtained.

The remaining part of this work is organized as follows: In Section2, architectural details of the proposed MAS-EMTS along with mathematical formulations are provided. For evaluation of the proposed MAS-EMTS, in Section3, a detailed simulation result analysis on two test cases is presented. Finally, the conclusion derived from the study is presented in Section4.

2. MAS-based electricity market trading simulator (MAS-EMTS)

MAS-EMTS is a modeling tool to study complex restructured electricity markets operation. It provides market players with simulation and decision-support resources, able to give them a competitive advantage in the market. As market players are complex entities, having their very own characteristics and objectives, making their decisions, and interacting with other players, MAS-EMTS was developed as a multi-agent-based simulation tool, modeling the complex dynamic market players, including their interactions and medium/long-term gathering of data and experience. MAS-EMTS uses neural network techniques, scenario analysis and optimization techniques to model market agents and to provide them with decision-support. MAS-EMTS purpose is to be able to simulate as many markets' models and player types as possible so it can reproduce in a realistic way of operation of real electricity markets. This enables it to be used as a simulation and decision-support tool for short/medium purposes but also as a tool to support long-term decisions, such as the ones taken by regulators.

2.1. Definition of a Multi-Agent system

Multi-Agent systems (MASs) are a new and exciting discipline in both Distributed Artificial Intelligence (DAI) and conventional computer science. A computerized system built of numerous interacting intelligent agents is known as a Multi-Agent System (MAS or "self-organized system"). Multi-Agent systems can tackle issues that a solitary agent would find difficult or impossible to solve. These systems are made up of agents, which are relatively autonomous and intelligent pieces. The generalized architecture of an agent is shown in Fig. 1, Even if we restrict ourselves to computer science, the word 'agent' has many meanings. MAS is simply a system that consists of two or more intelligent agents or agents. It is critical to understand that there is no overarching system aim, only the local goals of each actor. Multiple intelligent agents are required to implement the system designer's objectives, with local goals corresponding to sub-parts of that intention. Agents in a MAS may or may not be able to communicate directly with each other, depending on the definition of agency used. However, under Wooldridge's definitions, intelligent agents must have social ability and therefore must be capable of communicating with each other. Here agent is defined as a "hardware or (more usually) software-based computer system that enjoys the following properties:

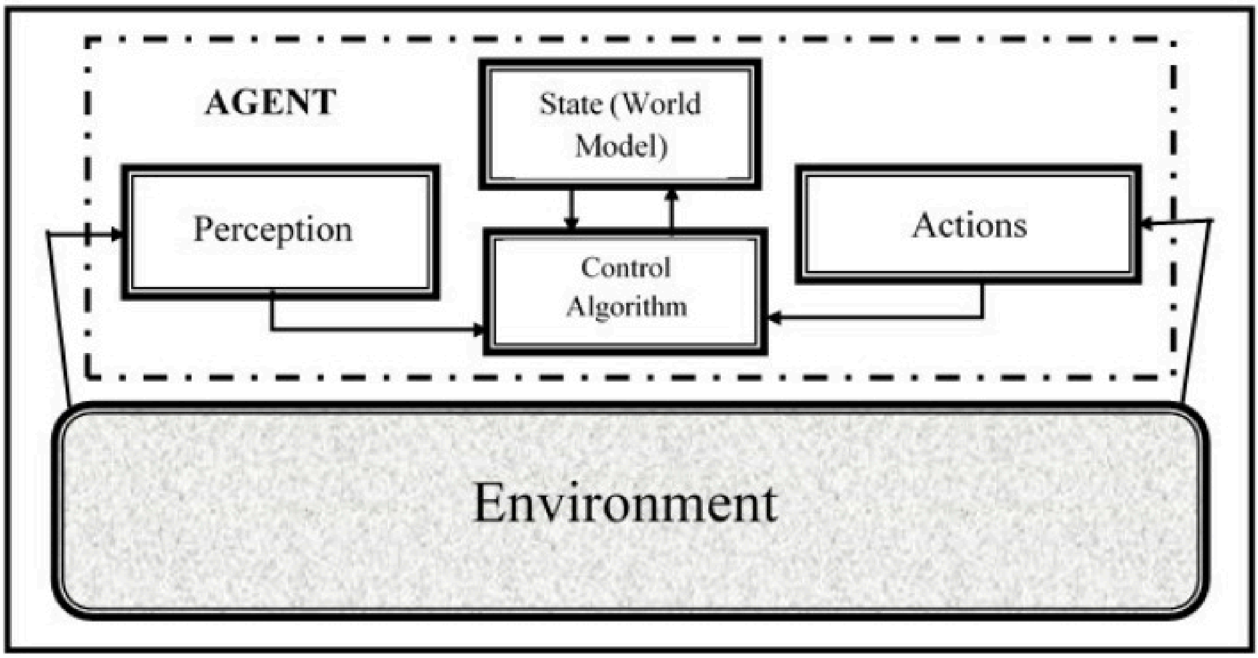

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Fig. 1. General architecture of an agent.

- **Autonomy:** Agents operate without the direct intervention of humans or others, and have some kind of control over their actions and internal state;
- **Social ability:** Agents interact with other agents (and possibly humans) via agent-communication language.
- **Reactivity:** Agents perceive their environment (which may be the physical world, a user via a graphical user interface, a collection of other agents, the internet, or perhaps all of these combined), and respond in a timely fashion to changes that occur in it.
- **Pro-activeness:** Agents do not simply act in response to their environment, they can exhibit goal-directed behavior by taking the initiative.
- **Computational ability:** Agents should be intelligent enough to derive a conclusion from the available data through modeling of the system. The computational ability of the agents is judged by the ability of the agent for developing rational decision-making models with the help of available real-world data.

Multi Agent-based software is particularly well fitted to analyzing dynamic and adaptive systems with complex interactions among their constituents. Several such modeling tools – designed to help researchers study restructured wholesale power markets – have emerged. We implement players in MAS as independent agents, with their ability to perceive the states and changes in the surrounding environment and to act accordingly. These agents are provided with bidding strategies, which must be adequate and refined to let them gain the highest possible advantage from each market context. MAS includes a complex simulation infrastructure that can cope with the diverse time scales of the supported negotiation mechanisms and with several agents competing and cooperating. Unlike traditional tools, MAS does not postulate a single decision maker with a single objective for the entire system. Rather, we allow agents representing the different independent entities in electricity markets to establish their objectives and decision rules. Moreover, as the simulation progresses, agents can adapt their strategies based on the success or failure of previous efforts. In each situation, agents dynamically adapt their strategies according to the present context and using the dynamically updated detained knowledge. MAS key players reflect actual entities from real markets and provide a means for aggregating consumers and producers.

2.2. MAS-EMTS

This agent-based structure employs a mathematical bidding emulator, forecaster, supervised architecture, and complexity reduction module. The said system comprises of mathematical bidding emulator that closely models market sentiments in terms of mathematical functions and finally mimics the competitive bidding scenario for executing the settlement rules. An optimal bid calculator agent is employed in the system to evaluate the profitable bids offered by the generating company. This agent utilizes the diverse data provided by the modeling agent to offer the optimal bids to the generating company. Further, the modeling data are provided to the supervised architecture for constructing an online decision-making architecture. The inputs of the system consist of rival bids for participating generating units and forecasted system demand.

2.3. MAS-EMTS architecture

A three-layer multi-agent architecture consisting of: The estimation Layer (EL), Control & Action Layer (CAL), and Real-time monitoring layer (RTML) has been proposed for bidding price simulator in a day ahead electricity market. The block diagram representation for this MAS is shown in Fig.2.

- **Estimation Layer (EL):-**This layer comprises two different types of agents like Rival Cost modeling agents (RCMA's) and Demand anticipating agents (DAA's).
- **Control** & **Action Layer (CAL):-** In this layer, Optimal Bid calculating agents are deployed and input to this layer is the data gathered from EL. Also, in this layer training agents are present which take input from the EL and by interaction produce Market Clearing Price (MCP) agent, Profit agent, and N-Block bid agents.
- **Real Time Monitoring Layer (RTML):-** This layer collects real-time information from the system and is formed by an Artificial Neural based Agent (ANBA) which provides the corrective action to the CAL.

The next section describes the various agents involved in these layers to solve the bidding problem in detail.

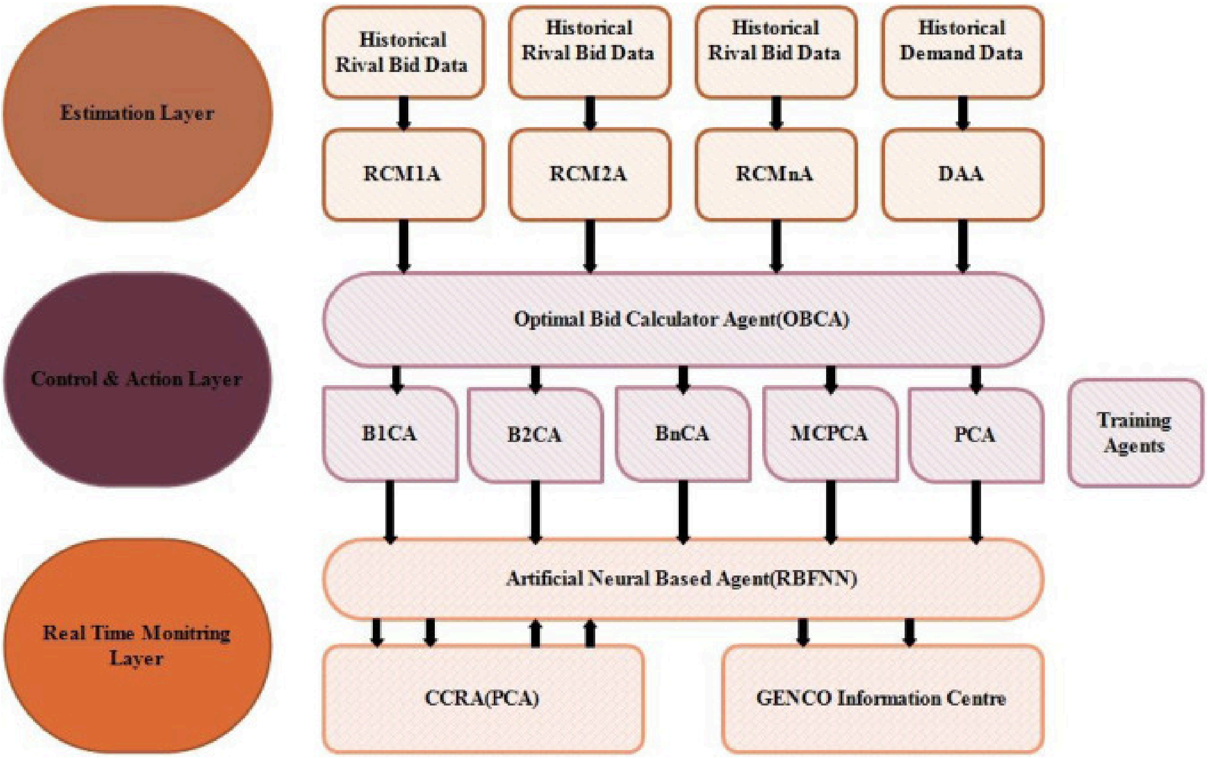

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Fig. 2. Proposed MAS-EMTS architecture.

2.4. Agents involved in proposed MAS-EMTS

In this section, various types of agents involved in the proposed MAS-EMTS are explained in detail:-

1. **Rival Cost Modeling Agents (RCMAs):-**These agents are used to formulate the rival's cost matrices using the Normal Probability Distribution function as it was used in[30], [31]. The normal distribution function is given by the equation below:

$$pdf\left(P_l^m\right) = \frac{1}{\sigma_l^m\sqrt{2\pi}}\exp\left(-\frac{\left(P_l^m-\mu_l^m\right)^2}{2\left(\sigma_l^m\right)^2}\right) \quad (1)$$

where σ_l^m and μ_l^m are the standard deviation and mean of bid price of mth rival for lth block. Here, we also generate the rivals' bid prices using different probability distribution functions. There is no loss of generality in generating data using other probability distributions.

2. **Demand Anticipating Agents (DAAs):-** These agents are responsible for anticipating demand using a normal probability distribution function.

3. **Optimal Bid Calculator Agents (OBCAs):-** To make an intelligent bidding price simulator for the day-ahead energy market. This agent involves interaction among various electricity market entities. The total cost of GENCO-G is given as

$$\begin{aligned} C_m\left(t\right) = {C_m}^p\left(t\right) + {C_m}^u\left(\chi_m\left(t\right)\left(1-\chi_m\left(t-1\right)\right)\right) \\ + {C_m}^d\left(1-\chi_m\left(t\right)\right)\chi_m\left(t-1\right) \end{aligned} \quad (2)$$

where

$$C_m{}^p(t) = a(P_m(t))^2 + bP_m(t) + c + d\left|\sin\left(e\left(\overline{P}_m - P_m(t)\right)\right)\right| \quad (3)$$

$$C_m{}^u = C_h + C_c\left(1 - \exp\left(-\frac{T_{off}}{T_c}\right)\right) \quad (4)$$

The net earnings of a GENCO are calculated by subtracting the total cost from revenue.

The steps involved in this process are given below:

- Step 1:- *Define actual generation cost and the capacity*

Define the actual cost function of GENCO-G with the possible production interval.

- Step 2:- *GENCO strategic/reported bidding in the wholesale electricity market.*

Calculate the reported market clearing price using an optimization algorithm named opposition theory based Moth Flame Optimizer[32] by taking the objective function as given below:

$$Maximize PR(MCP(t), P_m(t)) = \sum_{t=1}^{H}\sum_{m=1}^{M}[MCP(t) * P_m(t)] - C_m(t) \quad (5)$$

Subject to:

i. Power Limits:

$$\underline{P}_m(t)\chi_m(t) \le P_m(t) \le \overline{P}_m(t)\chi_m(t) \quad \forall t \in H \quad (6)$$

ii. Minimum Up and Down Time constraints

$$(1 - \chi_m(t+1))MUT_m \le \alpha_m{}^{on}(t) \quad if \quad \chi_m(t) = 1 \quad (7)$$

$$\chi_m(t+1)MDT_m \le \alpha_m{}^{off}(t) \quad if \quad \chi_m(t) = 0 \quad (8)$$

iii. Limitation on Bid Price

$$C_m(t) \le q_m(t) \le q_{\max} \quad \forall t \in H \quad (9)$$

- Step:3:- *Obtain the reported cost parameters of the GENCO-G using the same optimization routine.*:- Determine generator cost characteristics with optimized values of generator cost coefficients.

- Step:4:- *Determination of GENCOs' new production cost.*:- Determine the new marginal cost with parameters a, b, and c using Eq.(5) to bid in the electricity market.

In this particular manner, OBCA works to find an optimal bid for GENCO-G.

4. **Training Agents (TA):-** This agent works as a Normalizer for data obtained from the above Optimal calculator agent. To normalize data we use Min–max normalization of data variables and fed this

normalized data to the Radial Basis Function Neural Network (RBFNN) which is the heart of the next agent simulator.

5. **Artificial Neural based Agent (ANBAs):-** This agent is based on the RBFNN approach to solving the optimal bidding problem in a day ahead market. This agent serves two purposes:

- Firstly, it accumulates all the data coming from training agents and processes it for constructing the input matrix. This input matrix consists of rival bid data of generator (block-wise) for particular hour ‘t’ and demand data for that particular hour.

- Secondly RBFNN is constructed through the output in terms of MCP, generator’s cost characteristics coefficients, and profit obtained for an hour ‘t’.

RBFNN is chosen as an Artificial Neural Based Agent the reason that the mathematical relation of each node in the hidden layer can be identified easily in this net as compared to Multi-Layer Perceptron (MLP). Learning of the network is much faster in the case of RBFNN as compared to MLP. Lastly, the choice of several hidden nodes and layers is not a problem in RBFNN. Unlike other topologies of Neural Networks, this agent has superior scalability properties i.e.with the increase of the system parameters the performance of the system is not compromised.

6. **Computational Complexity Reduction Agents (CCRAs):-** Bid Prices of GENCO-G have been effectively calculated using historical data of Rival’s bid prices and demand values with highly efficient OBCA and ANBA. The influence of all rival’s bid data on the prediction of profit and bid prices of GENCO are not equal. Incorporating all these factors into the Artificial Neural based agent modeling will cause a heavy computational burden. To establish an accurate bid predictive model, it is necessary to select the major factors affecting the bid price forecasting using the well-known Principal Component Analysis (PCA). The function of PCA is to ensure minimal loss of rival’s bid and demand information and to reduce the dimensionality of the high-dimensional data performed on an Artificial Neural based agent. In using the PCA, the observation matrix is first defined as

$$=\begin{bmatrix} P_1 & P_2 & \cdots & P_{n-1} & P_n \end{bmatrix}\begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n-1} & p_{1n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ p_{k1} & p_{k2} & \cdots & p_{kn-1} & p_{kn} \end{bmatrix} \tag{10}$$

where the number of samples is chosen to be k = 1030; $P_1; P_2; P_3$.....P_n corresponds to the historical data of all rivals’ bid prices and demand, respectively; each line of P is corresponding to a sample. Then, the normalized sample data P^* is calculated as

$$p_i{}_j^* = \frac{p_{ij}-\overline{P_j}}{\sqrt{var(P_j)}} \tag{11}$$

where $\overline{P_j} = \frac{\sum_{i=1}^{k} p_{ij}}{k}$, $\mathrm{var}(P_j) = \frac{\sum_{i=1}^{n}\left(p_{ij}-\overline{P_j}\right)^2}{n-1}$ Thus, the sample correlation coefficient matrix for calculating the main component is given by

$$\mathrm{R} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n-1} & r_{1n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ r_{k1} & r_{k2} & \cdots & r_{kn-1} & r_{kn} \end{bmatrix} \tag{12}$$

$$r_{ij} = \frac{\sum_{m=1}^{n}\left(p_{ki}^{*} * p_{kj}^{*}\right)}{n-1} \quad (13)$$

Let λ_1; λ_2; λ_3; λ_4 be the eigenvalues of R, the contribution rate of the mth principal component can be computed by

$$\beta_m = \frac{\lambda_m}{\sum_{m=1}^{k} \lambda_m} \quad (14)$$

and the contribution rate of the first m main components is given by

$$\beta(k) = \frac{\sum_{i=1}^{m} \lambda_m}{\sum_{i=1}^{n} \lambda_m} \quad (15)$$

So in this way, computational complexity is reduced by selecting m principle components that highly influence the profitable bid prices of GENCO-G.

The next subsection describes the attributes of the proposed MAS-EMTS.

2.5. Attributes of proposed MAS-EMTS

The attributes of the proposed MAS-EMTS are as follows:-

1. The proposed MAS-EMTS employs a knowledge modeling attribute. This knowledge is imparted through scenario generation with the help of Monte Carlo Simulations, Demand variations (while closely observing the forecasted system demand) at the time of execution of the bidding process, and description of market operating conditions. With the help of this knowledge modeling, the proposed MAS-EMTS can yield profitable results for GENCO-G

2. For developing a practical MAS especially when the profit of any generating company is linked with the performance of the MAS, it is quite inevitable to check on the scalability property of the MAS. Scalability of the MAS can be determined by checking the performance degradation of an individual agent due to the expansion of the problem. In other words, the average measure of the degree of performance degradation of individual agents can be a potential denominator for depicting the scalability attribute of MAS. The proposed MAS-EMTS has been tested over two test cases, one with less no. of rival units and the other with higher no. of rival generators.

3. The proposed MAS-EMTS is a well-coordinated system, having intra-agent dependencies. Normally, the MAS agents use the coordination property for distributed expertise, resources, and information sharing. The proposed MAS-EMTS has several agents that possess intra-agent dependencies.

2.6. Advantages of MAS-EMTS

There are some disadvantages and drawbacks, compared to traditional software systems are limited predictability, understandability, and control accident- and error-prone system restricted reliability for computational purposes in spite of these MAS-EMTS has offered major advantages which are as follows:

1. MAS as an approach to the construction of robust, flexible, and extensible systems.

2. Distributed architecture: The nature of the distributed generation fits into the MAS architecture schemes relying on local information and decision-making.

3. MAS enables flexibility in several ways: plug and play capabilities to change the system and heterogeneous types of agents modeling heterogeneous sources and loads.

4. Resiliency: MAS can quickly respond and adjust to system conditions in real-time. Additionally, changes in network topology (a load or generator being disconnected) will not interrupt both local and global system objectives (e.g.,stability and efficiency).

3. Simulation results

MAS-EMTS has been constructed as depicted in the previous section. The proposed architecture has been used to obtain profitable bids for a generating company. Hence, this architecture and its sub-modules help the generating company to anticipate volatile market conditions and exploit them for gaining more profit. The results obtained by MAS-EMTS for the strategic bidding problem of generating companies are discussed in this section. First, results are reported for original MAS-EMTS which is of high dimension, secondly comparison results with other state of art approaches and in last subsection, results are represented for reduced dimensional MAS-EMTS.

3.1. Simulation results for original MAS

Two different Test systems, Test Case-1 and Test Case-2 have been considered here which are taken from [32].

First, it is implemented on Test Case-1 with three different demand levels in the range of 200–2200(1200) MW,700–2400(1700) MW, and 1200–3200(2200) MW.

Secondly, it is tested on Test Case-2 for three different cost models: namely: Cost Model-I which has a mean and standard deviation of all the rival bid prices that are the same. Cost Model-II: which has different mean values for all the rival bid prices and the standard deviation of all the rival bid prices are the same. Cost Model-III has both mean and standard deviation of rival bid prices that are different. These all-cost models are also analyzed for different demand levels in the range of 2000–4000(3000) MW, 3500–5500(4500) MW, and 5500–7500(6500) MW.

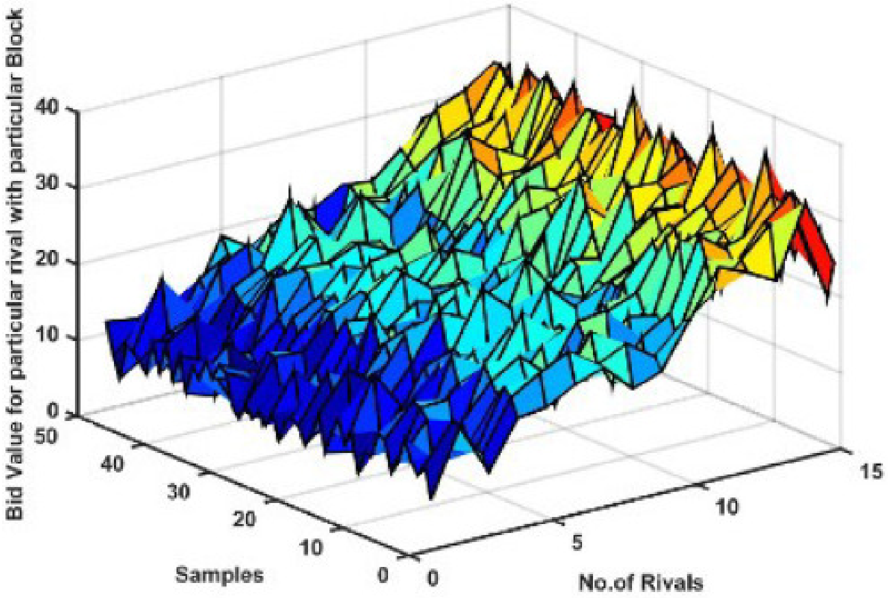

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Fig. 3. Rival Cost behavior for Test Case-1 for 200–2200MW demand.

All generators of the system participate in a single-sided auction. GENCO- G, bids in a spot market to earn more profit with the help of the proposed MAS-EMTS. The market accepts the bids in five blocks and data related to the bid is taken from[32]. The proposed MAS-EMTS works in three layers which are described earlier. While the settlement of energy bundles, Market Clearing Price (MCP) is obtained from Uniform Pricing Rule[32]. For establishing the supervised framework in one of the layers, RBFNN[33] is employed.

A supervised architecture is constructed by varying rival bids and system demand in a specific range. The supervised architecture is constructed with the help of 1030 samples of variable demand and rival bids. Different cost models are considered for generating data samples of rival bids. The rival cost modeling agent performs this task by considering the normal probability distribution function.

The first layer of MAS-EMTS is EL as described earlier. In this phase, two agents RCMA and DAA perform the task of calculating rival bids and demand. For creating rival bids, it is given that the market participants bid in five different blocks of different capacities. The normal distribution function is employed to generate 1030 samples of rival bids. The size of these rival matrices is (1030 *15) for Test Case-1 and (1030*30) for Test Case-2 which represents historical data of bid behavior in the spot market. The sample response of RCMA for the first 50 samples for Test Case-1 in the demand range of 200–2200MW is shown in Fig.3.

From the figure, it can be observed that these bids are numerically separated and can be used as a potential database for executing profitable bids for GENCO-G. A similar database is obtained with other cases also. The second agent of this phase is employed to generate the variable system demand.

The second layer of proposed MAS-EMTS is Control & Action layer. In this phase, OBCA is employed to calculate winning bids of generating companies along with MCP and different relevant market conditions. This agent works with the help of an opposition theory enabled Moth Flame Optimizer (OB-MFO)[32]. This agent works in two phases.

- In the first phase, it calculates market settlement through the calculation of MCP and allocates different energy packets to concerned generating units.
- In the second phase, it gives the scheduling details of generating units. However, this is not very beneficial information for single-hour bidding. For long trading hours, especially for day ahead schedule, this information can be employed by generating companies to earn more profit through alteration in cost curve characteristics.

In the next layer, i.e.,in the real-time monitoring layer, variables associated with generator such as cost curves, rival bid prices, MCP, and profit obtained by the above layer is fed to this layer through training agents after normalization and then this data is processed by ANBA through RBFNN for getting profit-making bid prices and modified generator cost coefficients. As per Ref.[32], it is observed that the system remains intact during the bidding process and satisfies all the constraints about the reliability and security of the system.

All results are majorly divided into three parts which are based on three different analyses namely:

- Profit Value Analysis
- MAPE (Mean Absolute Percentage Error) Analysis
- Profit Error Analysis

So, all these analyses are presented as follows:

Table 1. Results obtained for Test Case-1 with various demand levels.

System demand	200–2200 MW		700–2700 MW		1200–3200 MW	
Parameter	Unknown sample-2		Unknown sample-2		Unknown sample-10	
	Simulated	Test	Simulated	Test	Simulated	Test
B1	9.50995	11.56110	8.59533	15.00000	7.52098	8.00000
B2	15.28317	14.00000	12.37240	14.00000	13.14040	14.04080
B3	22.16463	25.07450	32.38383	27.97262	24.14430	28.00000
B4	30.34349	29.57167	27.24103	25.00000	27.23792	26.75199
B5	42.77110	40.00000	49.55292	40.00000	44.23597	40.00000
a1	0.00156	0.00150	0.00155	0.00150	0.00151	0.00150
a2	0.00150	0.00150	0.00150	0.00150	0.00156	0.00150
a3	0.00150	0.00150	0.00110	0.00100	0.00095	0.00150
a4	0.00110	0.00142	0.00208	0.00100	0.00134	0.00146
a5	0.00105	0.00100	0.00134	0.00128	0.00158	0.00108
b1	29.57674	32.00000	33.38074	32.00000	32.67229	32.00000

System demand	200–2200 MW		700–2700 MW		1200–3200 MW	
Parameter	Unknown sample-2		Unknown sample-2		Unknown sample-10	
	Simulated	Test	Simulated	Test	Simulated	Test
b2	31.63278	32.00000	35.21096	32.00000	34.47358	32.00000
b3	16.28549	27.76215	9.76710	18.13464	9.25436	7.84949
b4	6.81569	20.46212	6.08582	11.12474	20.80567	25.99927
b5	8.56595	7.99005	5.28748	12.86951	26.38927	21.36269
c1	599.63605	600.00000	600.16121	600.00000	599.98786	600.00000
c2	598.83956	600.00000	601.17755	600.00000	600.62700	600.00000
c3	599.44591	600.00000	600.04439	600.00000	600.10704	600.00000
c4	599.19239	600.00000	599.47490	600.00000	598.56765	600.00000
c5	600.01389	600.00000	600.09784	600.00000	598.87126	600.00000
MCP	**19.60787**	**32.64651**	**34.01768**	**35.00000**	**25.43869**	**16.00000**
Profit	**12438.57858**	**13024.58903**	**13651.90086**	**12545.73423**	**13648.92192**	**12826.52897**

3.1.1. Profit value analysis

To investigate the performance of the proposed MAS-EMTS, first obtained profit values are analyzed for 15 test samples and all simulated and test values of profit are compared and results are shown only for the sample which provides the maximum simulated profit value with MCP, all block bid prices and generator modified cost characteristics.

It is observed that rival bids simulated through MAS are accurate. These bids can yield maximum profit. Along with the profit calculation, this agent also suggests the profitable modeling of the cost curves of the generator.

The MCP, Profit and Cost Coefficients for all five blocks are depicted in Table 1, Table 2, Table 3, Table 4. In these Tables B.1 – B.5 represents the results of bid prices for 5 blocks, a1–a5, b1–b5 and c1–c5 are the generator's cost coefficients. For Test Case-1 maximum simulated profit is given by unknown sample-6 for demand range 200–2200 MW, unknown sample-7 for demand range 700–2700 MW, and unknown sample-2 for demand range 1200–3200 MW.

Similarly, for Test Case-2, Cost Model-I, for demand level 2000–4000 MW, unknown sample-8 provides maximum profit having simulated numerical value 6004.3363 with MCP 19.449825. Similarly, for demand level 3500–5500 MW, unknown sample-8 provides a maximum simulated profit value of 15,750.0445 with a simulated MCP of 20.7287. In the same line of order, for demand level, 5500–7500 MW unknown sample-9 gives a maximum simulated value of profit i.e.,44,685.76948 with MCP 19.36846.

For Test Case-2, Cost Model-II, for demand level 2000–4000 MW, un-known sample-12 provides maximum profit having simulated numerical value 10,279.9621 with MCP 32.5397. Similarly, for demand level 3500–5500MW, unknown sample-9 provides the maximum simulated profit value 19,888.6664 with simulated MCP 22.4213. In the same line of order, for demand level,5500–7500MW unknown sample-12 gives a maximum simulated value of profit i.e.,36,278.5798 with MCP 22.8576.

Table 2. Results obtained for Test Case-2 (Cost Model-I) for different demand levels.

System demand	**2000–4000 MW**		**3500–5500 MW**		**5500–7500 MW**	
Parameter	**Unknown sample-2**		**Unknown sample-2**		**Unknown sample-10**	
	Simulated	**Test**	**Simulated**	**Test**	**Simulated**	**Test**
B1	11.937711	14.431708	10.29636	9.86324	12.05148	11.68963
B2	14.339718	14.000000	14.36926	15.87239	16.54070	19.91575
B3	28.070132	20.000000	20.95172	23.62540	23.01728	27.74721
B4	31.130320	32.000000	28.25288	30.35034	30.06830	32.00000
B5	48.686610	50.000000	44.45287	48.39072	39.64896	48.67734
a1	0.000992	0.001000	0.00107	0.00119	0.00101	0.00100
a2	0.000982	0.001000	0.00104	0.00100	0.00101	0.00100
a3	0.001552	0.001175	0.00114	0.00108	0.00100	0.00100
a4	0.001538	0.001045	0.00149	0.00105	0.00107	0.00100
a5	0.001041	0.001000	0.00146	0.00101	0.00158	0.00116
b1	6.984259	7.000000	6.99924	7.00000	7.00071	7.00000
b2	6.809832	7.000000	7.03699	7.00199	7.00007	7.00000
b3	10.516562	7.000000	6.82908	7.00000	6.99033	7.00000
b4	11.085049	7.000000	26.89456	22.11454	8.02228	7.00000
b5	17.095785	32.000000	8.96239	8.54433	16.36616	17.74381
c1	75.050567	75.000000	80.37180	75.00000	74.66130	75.80285
c2	76.306856	75.000000	75.52720	82.44764	77.02750	75.68385
c3	73.949146	75.000000	81.65855	81.66428	74.92839	75.00000
c4	74.713121	75.000000	83.78188	80.16856	74.55239	75.00000
c5	75.511143	75.000000	77.22297	81.70968	77.53826	75.00000
MCP	**19.449825**	**35.000000**	**20.72877**	**30.96332**	**19.36846**	**34.52069**
Profit	**6004.336359**	**5222.946621**	**15750.04450**	**13047.21124**	**44685.76948**	**41061.29815**

Table 3. Results obtained for Test Case-2 (Cost Model-II) for different demand levels.

System demand	2000–4000 MW		3500–5500 MW		5500–7500 MW	
Parameter	Unknown sample-2		Unknown sample-2		Unknown sample-10	
	Simulated	Test	Simulated	Test	Simulated	Test
B1	7.209378	15.000000	10.66506	9.69192	11.98893	10.04272
B2	17.638991	14.773650	14.92650	18.15232	17.17059	15.25335
B3	19.371640	20.000000	18.89445	20.40913	22.23704	22.05550
B4	27.184441	32.000000	26.61220	26.94121	25.83505	32.00000
B5	45.876174	48.505391	42.26197	44.49464	41.45172	50.00000
a1	0.001083	0.001000	0.00103	0.00100	0.00104	0.00100
a2	0.001011	0.001000	0.00098	0.00100	0.00103	0.00100
a3	0.001427	0.001000	0.00090	0.00100	0.00101	0.00100
a4	0.001520	0.001057	0.00140	0.00124	0.00086	0.00100
a5	0.001279	0.001000	0.00102	0.00103	0.00129	0.00110
b1	7.001934	7.000000	6.99994	7.00000	7.00058	7.00000
b2	6.594572	7.000000	6.89626	7.00000	7.00047	7.00000
b3	4.609273	7.000000	6.58545	7.00000	6.96398	7.00000
b4	12.120285	7.919108	15.35764	15.63016	5.79703	7.00000
b5	11.986390	7.000000	12.99018	17.12450	10.66118	7.68949
c1	85.693838	75.000000	73.26485	75.00000	87.85451	75.00000
c2	82.350293	75.000000	77.29024	75.00000	85.41874	75.00000
c3	80.718493	75.000000	76.75373	75.00000	78.46845	75.00000
c4	77.364927	75.000000	78.08073	75.00000	76.50823	75.00000
c5	76.660740	75.000000	75.31482	75.00000	81.10276	75.00000
MCP	**32.539712**	**19.874024**	**22.42135**	**16.98983**	**22.85769**	**28.78013**
Profit	**10279.962147**	**15214.803260**	**19888.66648**	**15806.56530**	**36278.57989**	**34452.73832**

Table 4. Results obtained for Test Case-2 (Cost Model-III) for different demand levels.

System demand	2000–4000 MW		3500–5500 MW		5500–7500 MW	
Parameter	Unknown sample-2		Unknown sample-2		Unknown sample-10	
	Simulated	Test	Simulated	Test	Simulated	Test
B1	11.75783	8.71367	10.67456	10.27798	13.87902	12.74917
B2	14.10141	15.28019	18.49379	14.69158	15.79615	14.22434

System demand	2000–4000 MW		3500–5500 MW		5500–7500 MW	
Parameter	Unknown sample-2		Unknown sample-2		Unknown sample-10	
	Simulated	Test	Simulated	Test	Simulated	Test
B3	20.86703	20.27447	19.40563	20.00000	23.22109	21.89942
B4	33.35366	28.36694	27.75171	25.00000	32.15820	32.00000
B5	46.78420	48.25308	45.33610	50.00000	48.08532	40.57489
a1	0.00104	0.00100	0.00125	0.00100	0.00100	0.00100
a2	0.00102	0.00107	0.00107	0.00100	0.00103	0.00100
a3	0.00117	0.00105	0.00099	0.00100	0.00104	0.00100
a4	0.00129	0.00125	0.00126	0.00122	0.00101	0.00100
a5	0.00123	0.00117	0.00120	0.00100	0.00142	0.00150
b1	6.98696	7.00000	6.99935	7.00000	6.99870	7.00000
b2	6.61413	7.00000	9.11467	7.00000	7.00029	7.00000
b3	13.30070	7.00000	5.55937	7.00000	7.96281	7.00000
b4	14.11458	25.03692	19.48489	32.00000	9.67870	7.00000
b5	12.84040	22.09252	16.23020	13.38190	5.47209	9.22381
c1	75.99498	76.79115	78.43804	75.00000	78.01761	75.00000
c2	76.94924	75.00000	80.31391	75.00000	71.12739	75.00000
c3	76.02727	89.98772	77.15487	75.00000	74.92737	75.00000
c4	75.73814	75.62094	87.90296	75.00000	73.88480	75.17997
c5	77.85471	77.49914	76.06448	75.00000	76.65901	75.00000
MCP	**28.12816**	**27.89315**	**20.37714**	**24.10871**	**23.34817**	**21.56962**
Profit	**7744.48811**	**13795.96514**	**13253.53069**	**15521.49719**	**30969.78094**	**35982.38296**

In the same line of order, for Cost Model-III, for demand level 2000–4000MW, unknown sample-2 provides maximum profit having simulated numerical value 7744.4881 with MCP 28.1281. Similarly, for demand level 3500–5500MW, unknown sample-13 provides the maximum simulated profit value 13,258.1021 with simulated MCP 24.2996. In the same line of order, for demand level, 5500–7500MW unknown sample-10 gives a maximum simulated value of profit i.e.30,969.7809 with MCP 23.3481. Based on the above-reported results, the energy operator can operate the generating unit as per obtained cost coefficients. In a way, this MAS-EMTS not only suggests the profitable bid pattern to the generating company but also shows the pathway for obtaining optimal operation.

Table 5. Error analysis for Test Case-1.

Parameter	200–2200 MW	700–2700 MW	1200–3200 MW
B1	4.05E + 01	3.00E + 01	1.76E + 01
B2	1.72E + 01	6.42E + 00	1.17E + 01
B3	3.06E + 01	1.22E + 01	1.18E + 01
B4	1.25E + 01	8.18E + 00	8.93E + 00
B5	1.28E + 01	9.22E + 00	2.42E + 01
a1	1.11E + 01	1.91E + 00	9.14E−01
a2	1.91E + 01	1.59E + 00	2.46E + 00
a3	1.78E + 01	2.20E + 01	1.47E + 01
a4	2.89E + 01	3.08E + 01	1.74E + 01
a5	1.39E + 01	1.26E + 01	2.81E + 01
b1	2.55E + 01	4.00E + 00	1.05E + 00
b2	2.76E + 01	6.69E + 00	1.16E + 01
b3	2.47E + 01	2.19E + 01	5.62E + 01
b4	5.32E + 01	2.86E + 01	3.09E + 01
b5	3.32E + 01	2.96E + 01	5.85E + 01
c1	1.86E−01	7.14E−02	1.35E−01
c2	7.10E−01	7.80E−02	1.35E−01
c3	1.86E−01	5.92E−03	2.27E−01
c4	7.02E−02	4.20E−02	3.22E−01
c5	5.89E−02	4.39E−02	1.86E−01
MCP	**2.79E + 01**	**2.44E + 01**	**4.45E + 01**
Profit	**2.93E + 01**	**4.25E + 00**	**6.05E + 00**

3.1.2. MAPE analysis

This analysis indicates anticipating capability of the proposed system. The anticipation ability of the proposed system is evaluated through the calculation of error indices for different unknown samples out of 15 remaining testing samples. These MAPE values are calculated for both the Test-Cases which are given in Table 5, Table 6, Table 7, Table 8.

From all the reported results, it is observed that the results of the proposed MAS-EMTS are aligned with the optimization agent. From the results, it can be observed that MAPE is optimal for Profit. Hence, it is concluded that the proposed supervised architecture can be employed by GENCO for estimating accurate bids to achieve higher profits.

The prediction parameters for MAPE analysis are presented in Table 9. For this analysis, 4 parameters are set to predict network performance. The following conclusions are drawn from this analysis:

- Fig. 4 shows the analysis based on the Lewis criterion for Test Case-1 with various demand levels as described earlier. The MAS prediction based on this criterion is depicted along with the prediction quality in this figure. It is observed that for a system demand of 3000 MW, the quality of prediction is reasonable because 9 out of 22 parameters fall under this criterion. But For 4500 and 6500 MW demand, it is observed that the quality of prediction is excellent because 13 out of 22 and 10 out of 22 for 4500 and 6500 MW respectively fall in this category. For all demand levels of this Test Case, it is observed that only 1 such case is found in 3000 MW and 2 such cases are found in 6500 MW where the accuracy of the MAS falls (unacceptable criterion).

- Fig. 5 shows the analysis based on the Lewis criterion for Cost Model- I with various demand levels as described earlier. The MAS prediction based on this criterion is depicted along with the prediction quality in this figure. It is observed that for a system demand of 3000 MW, the quality of prediction is excellent because 12 out of 22 parameters fall in the excellent criterion. The same trend is observed by visualizing the results of 4500 MW and 6500 MW levels. For all demand levels of this Cost Model-I, it is observed that no such cases are found where the accuracy of the MAS falls under unacceptable criteria. It is also observed that MAS prediction is satisfactory.

- Fig. 6 shows the analysis based on the Lewis criterion for Cost Model-II with various demand levels as described earlier. The MAS prediction based on this criterion is depicted along with the prediction quality in this figure. It is observed that for a system demand of 3000 MW, the quality of prediction is excellent because 10 out of 22 parameters fall in the excellent criterion. A similar trend is observed by visualizing the results of 4500 MW and 6500 MW levels. For all demand levels of this Cost Model-II, it is observed that only 1 such case is found where the accuracy of the MAS falls under unacceptable criterion. It is also observed that MAS prediction is satisfactory.

- Fig. 7 shows the analysis based on the Lewis criterion for Cost Model-III with various demand levels as described earlier. The MAS prediction based on this criterion is depicted along with the prediction quality in this figure. It is observed that for a system demand of 3000 MW, the quality of prediction is excellent because 11 out of 22 parameters fall in the excellent criterion. The same trend is observed by visualizing the results of 6500 MW levels. For 4500 MW it is observed that 11 out of 22 parameters fall in the good category, and 7 out of 22 parameters fall in the excellent region. For all demand levels of this Cost Model-III, it is observed that only 1 such case is found where the accuracy of the MAS falls (unacceptable criterion).

By observing the results, it is concluded that this analysis proved the supremacy of the proposed MAS-EMTS for both the Test Cases.

Table 6. Error analysis for Cost Model-I (Test Case-2).

Parameter	2000–4000 MW	3500–5500 MW	5500–7500 MW
B1	1.84E + 01	2.15E + 01	2.03E + 01
B2	6.39E + 00	1.49E + 01	2.84E + 01
B3	3.41E + 01	7.47E + 00	1.46E + 01
B4	9.17E + 00	1.18E + 01	3.38E + 00
B5	1.55E + 01	1.10E + 01	1.91E + 01
a1	7.06E + 00	1.16E + 01	1.73E + 00
a2	1.89E + 00	5.70E + 00	9.82E−01
a3	3.33E + 01	1.18E + 01	2.54E−01
a4	2.23E + 01	2.37E + 01	1.12E + 01
a5	1.53E + 01	2.23E + 01	3.09E + 01
b1	5.38E−01	2.22E−02	1.43E−02
b2	2.56E + 00	1.02E + 01	2.04E−03
b3	4.54E + 01	4.00E + 01	1.65E−01
b4	3.48E + 01	3.28E + 01	2.08E + 01
b5	4.51E + 01	2.29E + 01	2.83E + 01
c1	7.56E−01	1.42E + 01	1.65E + 00
c2	1.07E + 00	7.83E + 00	2.54E + 00
c3	1.88E + 00	3.07E + 00	1.21E + 00
c4	6.97E−01	3.26E + 00	2.61E + 00
c5	1.53E + 00	5.53E + 00	2.22E + 00
MCP	**3.50E + 01**	**3.01E + 01**	**3.55E + 01**
Profit	**8.54E + 00**	**2.97E + 01**	**5.06E + 00**

Table 7. Error analysis for Cost Model-II (Test Case-2).

Parameter	2000–4000 MW	3500–5500 MW	5500–7500 MW
B1	3.25E + 01	1.33E + 01	1.71E + 01
B2	4.91E + 00	1.97E + 01	1.33E + 01
B3	1.49E + 01	1.33E + 01	2.53E + 01
B4	1.05E + 01	1.29E + 01	1.14E + 01
B5	1.39E + 01	7.17E + 00	1.39E + 01

Parameter	2000–4000 MW	3500–5500 MW	5500–7500 MW
a1	5.56E + 00	1.50E + 01	9.30E + 00
a2	1.62E + 00	3.87E + 00	5.31E + 00
a3	2.07E + 01	7.81E + 00	9.84E−01
a4	2.75E + 01	2.00E + 01	3.13E + 01
a5	1.66E + 01	1.04E + 01	1.75E + 01
b1	9.27E−03	5.55E−02	9.29E−02
b2	6.25E + 00	5.42E + 00	1.56E−02
b3	3.54E + 01	1.34E + 01	1.85E + 00
b4	5.03E + 01	3.55E + 01	3.60E + 01
b5	3.65E + 01	4.54E + 01	3.12E + 01
c1	4.77E + 00	9.41E + 00	1.42E + 01
c2	4.02E + 00	6.36E + 00	6.78E + 00
c3	2.38E + 00	6.08E + 00	5.90E + 00
c4	1.58E + 00	1.28E + 01	8.29E + 00
c5	1.91E + 00	8.42E + 00	8.80E + 00
MCP	**3.12E + 01**	**2.64E + 01**	**1.42E + 01**
Profit	**1.68E + 01**	**1.76E + 01**	**1.59E + 01**

Table 8. Error analysis for Cost Model-III (Test Case-2).

Parameter	2000–4000 MW	3500–5500 MW	5500–7500 MW
B1	2.19E + 01	2.28E + 01	1.85E + 01
B2	4.39E + 00	1.83E + 01	1.18E + 01
B3	9.56E + 00	1.70E + 01	7.94E + 00
B4	1.07E + 01	5.29E + 00	5.94E + 00
B5	1.21E + 01	1.18E + 01	1.37E + 01
a1	2.14E + 00	1.00E + 01	5.34E−01
a2	3.40E + 00	3.24E + 00	2.50E + 00
a3	3.20E + 01	1.32E + 01	1.84E + 00
a4	1.74E + 01	1.22E + 01	1.58E + 01
a5	1.94E + 01	1.76E + 01	1.17E + 01
b1	3.25E−01	1.06E−02	1.97E−02

Parameter	2000–4000 MW	3500–5500 MW	5500–7500 MW
b2	4.76E + 00	1.17E + 01	1.02E−02
b3	3.53E + 01	1.40E + 01	4.89E + 00
b4	5.22E + 01	2.80E + 01	2.55E + 01
b5	3.29E + 01	2.48E + 01	2.57E + 01
c1	6.34E−01	1.03E + 01	4.18E + 00
c2	1.20E + 00	6.07E + 00	4.42E + 00
c3	3.66E + 00	4.00E + 00	4.52E + 00
c4	4.66E−01	9.16E + 00	5.27E + 00
c5	1.45E + 00	5.71E + 00	4.40E + 00
MCP	**3.10E + 01**	**2.87E + 01**	**2.41E + 01**
Profit	**2.07E + 01**	**1.74E + 01**	**1.04E + 01**

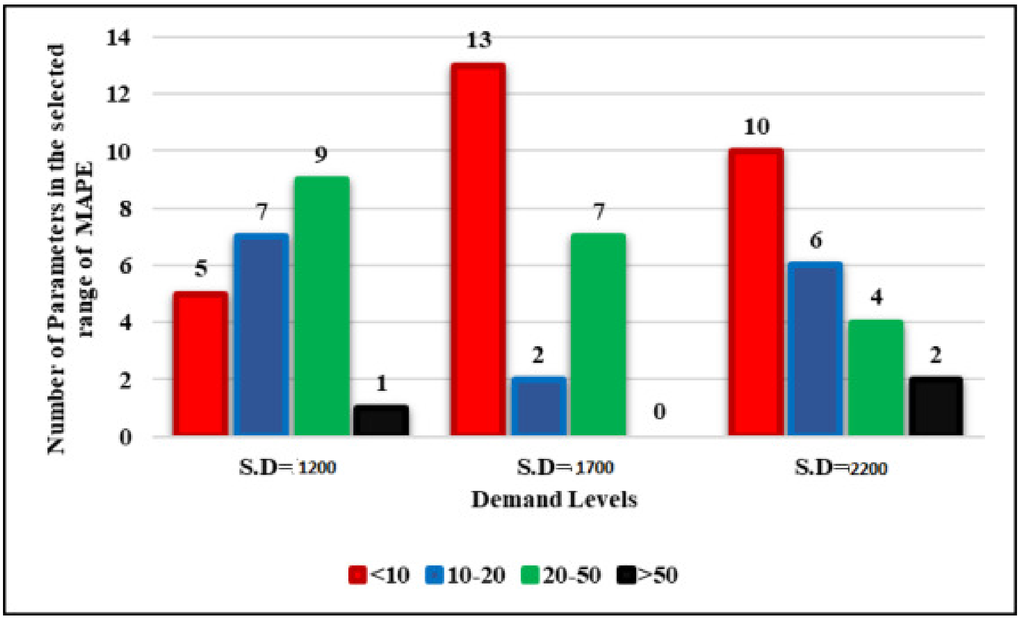

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Fig. 4. Error Analysis for profit of generating company for Test Case-1 for different demand levels.

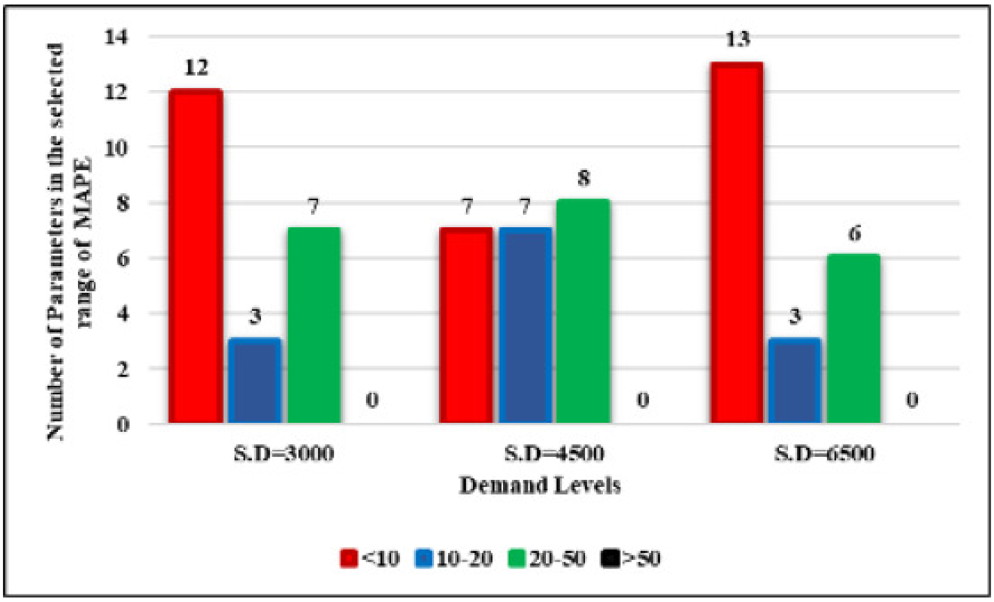

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Fig. 5. Error Analysis for profit of generating company for Cost Model-I of Test Case-2 for different demand levels.

Table 9. MAPE prediction parameters.

MAPE(%)	**<=10**	**10–20**	**20–50**	**>=50**
Prediction precision	Excellent	Good	Reasonable	Unacceptable

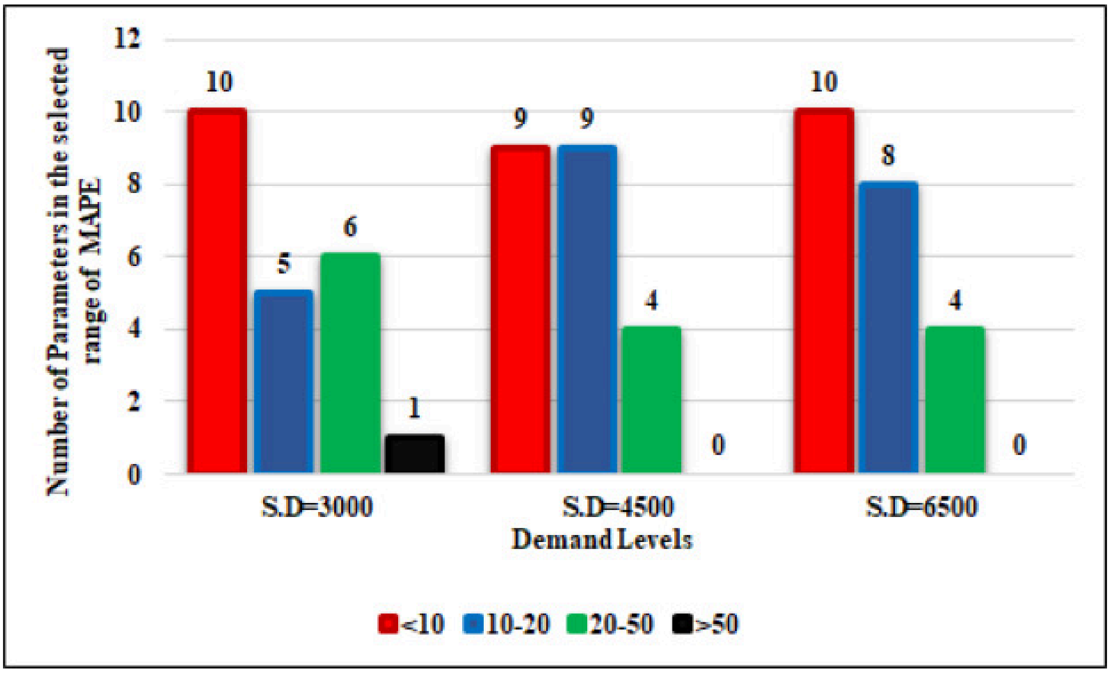

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Fig. 6. Error Analysis for profit of generating company for Cost Model-II of Test Case-2 for different demand levels.

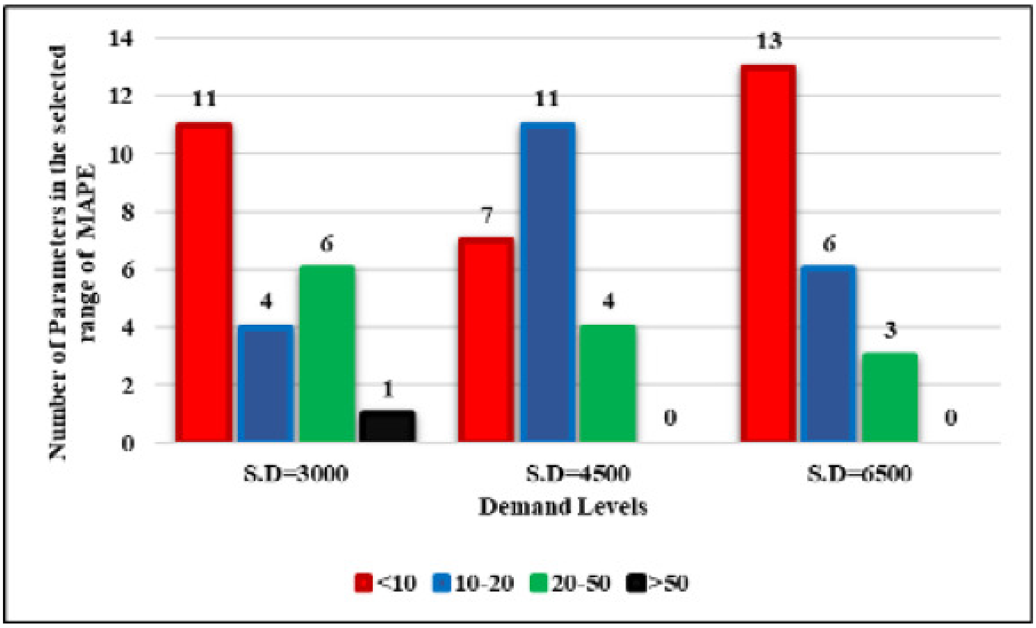

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Fig. 7. Error Analysis for profit of generating company for Cost Model-III of Test Case-2 for different demand levels.

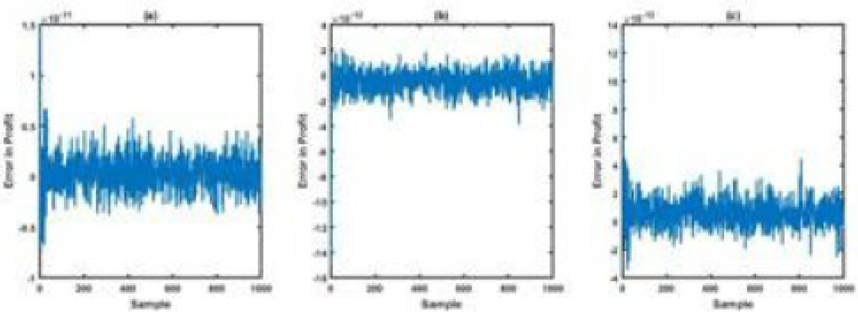

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Fig. 8. Profit Error Analysis for Test Case-1 for (a)1200 MW (b) 1700 MW (c) 2200 MW demand levels.

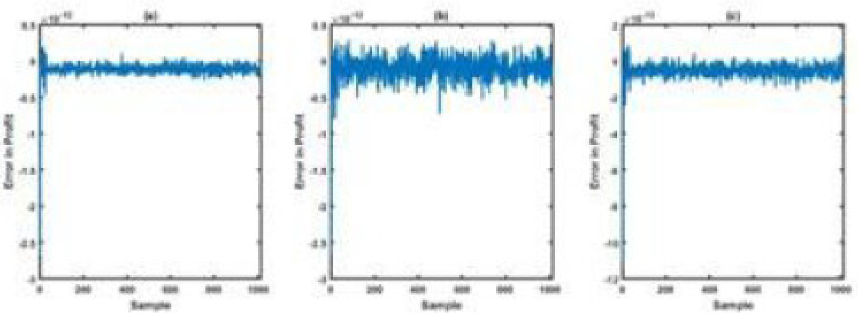

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Fig. 9. Profit Error Analysis for Cost Model-I (Test Case-2) for (a) 3000 MW (b) 4500 MW (c) 6500 MW demand.

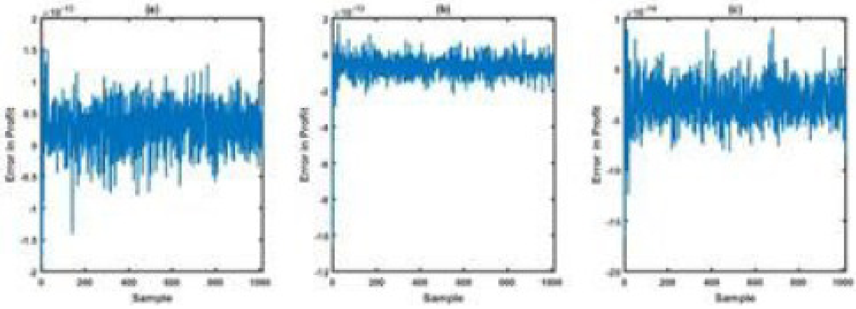

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Fig. 10. Profit Error Analysis for Cost Model-II (Test Case-2) for (a) 3000 MW (b) 4500 MW (c) 6500 MW demand.

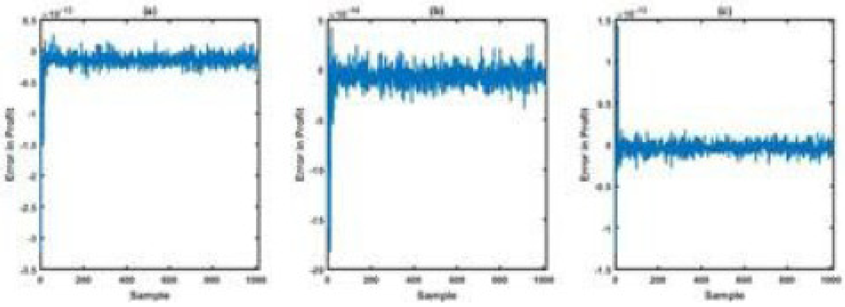

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Fig. 11. Profit Error Analysis for Cost Model-III (Test Case-2) for (a) 3000 MW (b) 4500 MW (c) 6500 MW demand.

3.1.3. Profit Error Analysis

Further, Error from network simulation in all parameters with 1030 samples is also obtained. The Fig. 8, Fig. 9, Fig. 10, Fig. 11 present the variations of error in obtained profit for both test cases which represents error in obtained profit is not very significant.

3.2. Comparison with other state of art approaches

The comparative results with other optimization techniques namely OB-MFO (Opposition theory inspired moth flame optimizer), MFO (Moth Flame Optimizer), ALO (Ant Lion Optimizer), SCA (Sine–Cosine Algorithm), and PSO (Particle Swarm optimizer) are presented in Table 10, Table 11, Table 12, Table 13 for both the cases. The results obtained from the agent-based simulation approach prove the supremacy of the proposed technique. The profit obtained i.e., 12,438.58 from Agent-based simulation for demand level 1200 MW for Test Case-1 is very much higher than other state of art approaches. Similar results are obtained for other demand levels. For Test Case-2 and with various cost models with various demand levels profit obtained from agent-based simulation is much higher than other optimization algorithms. So, results obtained from the simulator always support the agent-based based over another optimization algorithms.

The next section presents the analysis of reduced dimensional MAS by using the PCA methodology.

Table 10. Comparative analysis of obtained profit for Test Case-1 for different demand levels.

TECHNIQUES	Demand = 1200MW		Demand = 1700MW		Demand = 2200MW	
Agent based simulation	MCP	19.61	MCP	34.02	MCP	25.44
	Profit	**12438.58**	Profit	**13651.90**	Profit	**13648.92**
OB-MFO	MCP	18.17	MCP	23.82	MCP	31.01
	Profit	1710.20	Profit	3914.20	Profit	5218.90
MFO	MCP	17.82	MCP	22.79	MCP	30.45
	Profit	1615.80	Profit	3496.40	Profit	5023.70
ALO	MCP	17.57	MCP	21.98	MCP	30.93
	Profit	1575.24	Profit	3218.80	Profit	5169.70
SCA	MCP	17.11	MCP	22.82	MCP	29.69
	Profit	1512.61	Profit	3366.20	Profit	4967.20
PSO	MCP	15.98	MCP	20.06	MCP	27.98
	Profit	1240.54	Profit	2900.09	Profit	4321.97

Table 11. Comparative analysis of obtained profit for Test Case-2 for Cost Model-I for different demand levels.

TECHNIQUES	Demand = 3000MW		Demand = 4500MW		Demand = 6500MW	
Agent based simulation	MCP	**19.45**	MCP	**20.73**	MCP	**19.37**
	Profit	**6004.34**	Profit	**15750.04**	Profit	**44685.77**
OB-MFO	MCP	18.19	MCP	23.82	MCP	31.01
	Profit	2910.20	Profit	9612.20	Profit	19178.00
MFO	MCP	17.82	MCP	23.79	MCP	30.45
	Profit	2798.80	Profit	9596.40	Profit	18875.00
ALO	MCP	17.57	MCP	23.69	MCP	30.23
	Profit	2675.20	Profit	9588.80	Profit	18411.00
SCA	MCP	17.81	MCP	23.62	MCP	29.91
	Profit	2772.10	Profit	8166.20	Profit	18087.00
PSO	MCP	16.55	MCP	23.01	MCP	27.87
	Profit	2432.87	Profit	7984.60	Profit	16459.00

Table 12. Comparative Analysis of obtained profit for Test Case-2 for Cost Model-II for different demand levels.

TECHNIQUES	**Demand = 3000MW**		**Demand = 4500MW**		**Demand = 6500MW**	
Agent based simulation	MCP	32.54	MCP	22.42	MCP	22.86
	Profit	10279.96	Profit	19888.67	Profit	36278.58
OB-MFO	MCP	18.75	MCP	22.01	MCP	29.48
	Profit	3150.70	Profit	7215.80	Profit	17110.00
MFO	MCP	18.67	MCP	21.95	MCP	29.39
	Profit	3101.40	Profit	7108.90	Profit	16970.00
ALO	MCP	18.62	MCP	21.74	MCP	28.02
	Profit	3095.10	Profit	7041.70	Profit	14137.00
SCA	MCP	17.96	MCP	20.31	MCP	29.34
	Profit	2829.70	Profit	6182.10	Profit	16455.00
PSO	MCP	17.02	MCP	18.56	MCP	25.47
	Profit	2710.20	Profit	5563.90	Profit	12563.00

Table 13. Comparative Analysis of obtained profit for Test Case-2 for Cost Model-III for different demand levels.

TECHNIQUES	**Demand = 3000MW**		**Demand = 4500MW**		**Demand = 6500MW**	
Agent based simulation	MCP	22.79	MCP	24.30	MCP	27.12
	Profit	6830.53	Profit	13258.10	Profit	32505.92
OB-MFO	MCP	19.09	MCP	23.99	MCP	30.55
	Profit	3379.40	Profit	9874.60	Profit	18963.00
MFO	MCP	19.07	MCP	23.97	MCP	30.45
	Profit	3299.70	Profit	9788.80	Profit	18475.00
ALO	MCP	19.01	MCP	23.96	MCP	30.01
	Profit	3249.20	Profit	9707.90	Profit	17059.00
SCA	MCP	18.82	MCP	23.51	MCP	30.04
	Profit	3174.50	Profit	8104.30	Profit	18226.00
PSO	MCP	17.63	MCP	22.14	MCP	28.79
	Profit	2900.49	Profit	7864.90	Profit	15986.00

Table 14. Eigen Values and Contribution Rates for selected features of Test Case-2.

CASE	Cost Model-I (Demand-2000–4000 MW)		Cost Model-II (Demand-3500–5500 MW)		Cost Model-III (Demand-5500–7500 MW)	
Attributes	**Eigenvalues**	**Contribution-rate**	**Eigenvalues**	**Contribution-rate**	**Eigenvalues**	**Contribution-rate**
R1-B1	**1.323180128**	**4.268322993**	0.682223972	2.200722489	**1.337761769**	**4.315360546**
R2-B1	0.684859438	2.209223994	**1.30977872**	**4.225092646**	0.690515562	2.227469556
R3-B1	**1.272502445**	**4.104846598**	**1.277079716**	**4.119611987**	0.702794207	2.267078086
R4-B1	**1.258333073**	**4.059138946**	**1.260977508**	**4.06766938**	**1.299064578**	**4.190530898**
R5-B1	0.736201041	2.374842068	0.737766299	2.379891287	0.75031018	2.420355418
R6-B1	0.751652728	2.42468622	0.747789508	2.41222422	**1.248597313**	**4.027733269**
R1-B2	0.761465703	2.456340978	0.759013899	2.448431931	0.765173864	2.468302787
R2-B2	**1.227048416**	**3.958220697**	1.229217372	3.965217331	0.786750517	2.537904892
R3-B2	**1.219562031**	**3.934071068**	**1.214538742**	**3.917866909**	**1.208185053**	**3.897371139**
R4-B2	**1.186144673**	**3.826273137**	**1.189662586**	**3.837621247**	**1.205012487**	**3.887137056**
R5-B2	**1.172611491**	**3.782617714**	**1.174990571**	**3.790292163**	**1.188715937**	**3.834567539**
R6-B2	**1.16053076**	**3.743647613**	0.808479914	2.607999724	**1.169767737**	**3.773444313**
R1-B3	0.813285782	2.623502523	**1.145044742**	**3.693692717**	0.828052161	2.671136003
R2-B3	0.823431319	2.656230061	**1.122272492**	**3.620233846**	0.853512862	2.753267298
R3-B3	**1.136364969**	**3.66569345**	**1.119543607**	**3.61143099**	0.845379891	2.727031907
R4-B3	**1.117701926**	**3.605490084**	0.834448923	2.691770721	0.882226203	2.845890977
R5-B3	0.841828579	2.715576062	0.843161429	2.719875579	0.889712567	2.870040537
R6-B3	0.865753637	2.792753669	0.865820523	2.79296943	0.899224043	2.900722718
R1-B4	0.872574766	2.814757311	**1.078211758**	**3.478102444**	0.93708282	3.022847807
R2-B4	0.884951891	2.854683519	0.881000216	2.841936182	0.948576545	3.059924338
R3-B4	0.912078062	2.942187297	0.891419339	2.875546254	0.944580039	3.047032384
R4-B4	0.927706385	2.992601241	0.909404704	2.933563561	**1.134386614**	**3.659311659**
R5-B4	0.932495445	3.008049823	0.926296199	2.988052256	**1.121355313**	**3.617275204**
R6-B4	0.951044811	3.067886487	0.933621686	3.011682859	**1.099907197**	**3.548087731**
R1-B5	**1.073844956**	**3.464015987**	0.956914154	3.086819852	0.987711422	3.186165876
R2-B5	**1.053501944**	**3.398393368**	**1.056495722**	**3.408050716**	**1.082491129**	**3.491906868**
R3-B5	**1.043460579**	**3.366001868**	**1.047390172**	**3.378677975**	**1.061901626**	**3.425489115**
R4-B5	0.972863877	3.138270572	0.982324143	3.168787557	**1.047735351**	**3.379791454**

CASE	Cost Model-I (Demand-2000–4000 MW)		Cost Model-II (Demand-3500–5500 MW)		Cost Model-III (Demand-5500–7500 MW)	
Attributes	**Eigenvalues**	**Contribution-rate**	**Eigenvalues**	**Contribution-rate**	**Eigenvalues**	**Contribution-rate**
R5-B5	0.996142243	3.213362075	0.989637966	3.192380535	**1.039830075**	**3.354290563**
R6-B5	1.010116173	3.258439268	1.004718457	3.241027282	1.029642073	3.321426042
Demand	**1.016760725**	**3.279873306**	**1.020754959**	**3.292757933**	1.014042866	3.27110602

3.3. Simulation results of reduced dimensional MAS-EMTS

After successful implementation of the proposed MAS-EMTS in two test cases, it is observed that with the increase of the rivals and blocks in bidding, the size of the input matrix is substantially increased hence, the scalability of the proposed MAS-EMTS is limited. Enhancing the scalability of the proposed MAS-EMTS dimensionality reduction can be achieved by CCRA. The results of the implementation of the action of CCRA are depicted in Table 14 where contribution rates of input parameters are evaluated based on the Eigenvalues. Hence, for framing the reduced input matrix, the highest contribution rate inputs are chosen.

Based on contribution rate reduced features are obtained which are given in Table 15.

The following points can emerge from this analysis.

Table 15. Reduced complex system analysis.

Total features	Cost Model-I(2000–4000 MW)	Cost Model-II(3500–5500 MW)	Cost Model-III(5500–7500 MW)
	Features reduced	**Features reduced**	**Features reduced**
B1(R1-R6)	R1B1,R3B1,R4B1	R2B1,R3B1,R4B1	R1B1,R4B1,R6B1
B2(R1-R6)	R2B2,R3B2,R4B2,R5B2,R6B2	R3B2,R4B2,R5B2	R3B2,R4B2,R5B2,R6B2
B3(R1-R6)	R3B3,R4B3,	R1B3,R2B3,R3B3,	**N/A**
B4(R1-R6)	**N/A**	R1B4	R4B4,R5B4,R6B4
B5(R1-R6)	R1B5,R2B5,R3B5	R2B5,R3B5,R5B5	R2B5,R3B5,R4B5,R5B5
Demand	**Yes**	**Yes**	**N/A**
Total features=31	**14**	**14**	**14**

Table 16. Error indices for selected cases of Test Case-2.

Test-Case-2/Cost models	**Cost Model-I (Demand-3000 MW)**		**Cost Model-II (Demand-4500 MW)**		**Cost Model-III (Demand-6500 MW)**	
Error indices	**Network-1**	**Network-2 (With PCA)**	**Network-1**	**Network-2 (With PCA)**	**Network-1**	**Network-2 (With PCA)**
MSE	2.28E−20	8.25E−16	2.10E−20	2.03E−15	2.10E−22	2.88E−15
SSE	5.18E−16	1.87E−11	4.76E−16	4.61E−11	4.76E−18	6.52E−11
MAE	2.41E−11	5.24E−09	2.85E−11	6.04E−09	2.35E−12	9.07E−09

- For Test Case-2, with mean values of 3000 MW, it is observed that the highest contribution rates are for variables for block 1,(R1, R3 and R4) for block 2,(R2, R3, R4, R5, and R6) for block 3,(R3 and R4) for block 5,(R1, R2, and R3) and system demand. These variables are shown in boldface in Table 14. By choosing these 14 variables as input, the size of the input matrix can be drastically reduced hence the MAS can achieve relaxation in computational complexity. By observing various error indices depicted in Table 16, it is observed that the accuracy is not compromised as error indices of original MAS and Reduced feature MAS are falling in a narrow range.

- Further, the second case is considered with a mean value of demand of 4500 MW, it is observed that the highest contribution rates for variables for block 1,(R2, R3, and R4) for block 2, (R2, R3, R4, and R5) for block 3,(R1, R2, and R3) for block 4,(R1) for block 5, (R2 and R3) and demand. By choosing these 14 variables reduced dimensionality neural network can be framed, and it is observed that errors reported by this network and original MAS fall in a narrow range. A comparison of these errors is shown in Table 16.

- Further, the third case is considered with a mean value of demand of 6500 MW, it is observed that the highest contribution rates for variables for block 1,(R1, R4, and R6) for block 2, (R3, R4, R5, and R6) for block 4,(R4, R5, and R6) for block 5,(R2, R3, R4, and R5). It is observed that system demand is not having a contribution rate in this case, hence, that variable is omitted. By choosing these 14 variables reduced dimensionality neural network can be framed and it is observed that errors reported by this network and original MAS fall in a narrow range. A comparison of these errors is shown in Table 16.

For all these cases profit error representation is given in Fig. 12. This figure presents the variations of error in obtained profit for this reduced dimensional case which shows error in obtained profit is not very significant.

4. Conclusion

Multi-Agent Systems are valuable assets in dynamic conditions of power markets. Any generating company having such MAS can exercise market power as these are important tools to understand uncertainties. A MAS with diverse agent characteristics has been presented in this work. The following points summarize the contribution.

1. An MAS with five agents is proposed in this work. The characteristics of these agents along with the specific work are explained. These agents are namely RCMA, DAA, OBCA, ANBA, and CCRA.

2. An effort is made to simulate diverse market conditions by using DAA and RCMA. These agents make a dynamic scenario for the bidding process. In this process, system demand and rival bids are varied. Further, an optimization routine is established with the help of OBCA and optimal bids and market clearing price are obtained.

3. Further, by employing this data a supervised architecture is formed and profitable bids, and generator cost curve characteristics have been obtained. ANBA agent utilizes characteristics of the Radial Basis function to calculate these parameters for the bidding process.

4. Finally, after dimensional reduction, the proposed architecture has been tested for two test systems along with different cost models. Results reveal that proposed MAS-EMTS yields profitable results with less computation time.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

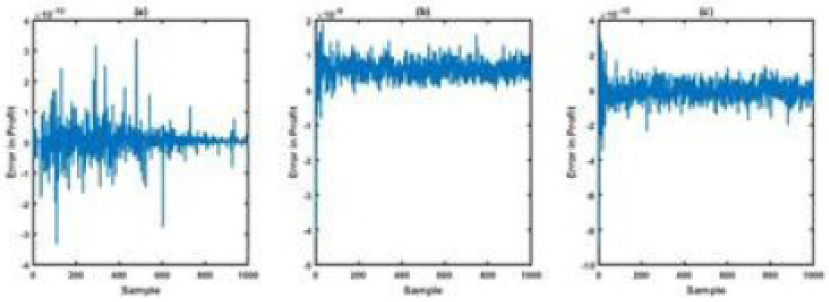

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Fig. 12. Profit Error Analysis for (a) Cost Model-I with 3000 MW (b) Cost Model-II with 4500 MW and Cost Model-III with 6500 MW demand after reduction in dimension.

Recommended articles

Data availability

Data will be made available on request.

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> …In (Ming et al., 2023), the Coupon-based Incentive Demand Response (CIDR) mechanism for small residential users is analyzed, focusing on the efficiency and social welfare of the mechanism, and introducing an Extra Incentive Term (EIT) to maximize social welfare. Finally (Jendoubi and Bouffard, 2023), explores advanced multi-agent RL approaches for demand management in complex energy systems (May and Huang, 2023), employs MARL-DR to optimize energy management in smart microgrids, and (Jain and Saxena, 2023) designs multi-agent system-based simulators to analyze electrical markets. In (Homod et al., 2023), a multi-agent approach is used in building heating systems, and (Sangoleye et al., 2023) explores the implementation of energy DR in buildings through price signals, using deep RL to optimize energy efficiency and emission reduction.…

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