

Leveraging Reinforcement Learning for Dynamic Pricing Models in E-Commerce

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ABSTRACT

Recurring and Machine learning (RL) is gradually gearing up as a prevailing technique to enhance dynamic pricing system in e-businesses. Past methodologies incorporate fixed or scripted models of price determination, which cannot analyze the intricacies of customer purchasing patterns, demand changes and competitor dynamics in real time. RL for an e-commerce platform to achieve dynamic pricing as it is an application of machine learning that learns from its environment. In the case of use of RL, businesses can obtain the best returns on sales as well as satisfy their clients through the setting of appropriate price information from inputs such as stock, client experience and other market conditions. In this paper, the author discusses the use of RL in the dynamic prices of e-commerce focusing on the dynamic prices algorithm and its flexibility in changing market and customers behavior. The presented challenge includes the balance between exploration and exploitation, problems with the scalability of the algorithm, the need to consider a long-term reward function. Such findings illustrate how RL applied to online retail platforms contributes to enhancing the working relationship between these enterprises and clientele, protecting revenues, enhancing price accuracy. Furthermore, the paper compares various RL models such as Q learning and deep reinforcement learning, and their applicability towards various pricing situations. The current work encourages that RL based dynamic pricing models can offer a higher return compared with conventional models due to more flexible price setting strategies offered by the former. But such models are only efficient and accurate as the data used, structure of the reward system, and real-time digestion of big data. This paper concludes with suggestions for future research and recommendations for the application of Reinforcement Learning in dynamic pricing for e-commerce enterprises.

Keywords: Reinforcement Learning, Dynamic Pricing, E-commerce, Revenue Optimization, Machine Learning.

I. INTRODUCTION

Pricing elasticity, today, assumes control over more innovative approaches to e-commerce, where dynamic pricing has now emerged as a definite technique for many companies to control their revenues and adapt to change. Dynamic pricing is quite different from conventional static forms of pricing because it adapts itself to changing conditions by using data on customer demand, inventory, and competitor actions. Continuing e-commerce environment complexity predisposes firms to harness such modern solutions as machine learning to improve price management. Among these, Reinforcement Learning (RL) has been considered one of the most crucial approaches to develop as it has the possibility of incorporating the ability to automate and learn how to optimize dynamic pricing over the act of continuous reinforcement learning process.

Reinforcement Learning is a subfield of machine learning wherein the system's interaction with an environment contributes to learning. In the case of dynamic pricing, RL algorithms can weigh through various prices, get a response in the form of rewards

profit or customer satisfaction, then use it in future iterative decisions. This characteristic of learning from and reacting to real-time data makes RL most appropriate for e-commerce markets, which are rapidly competitive. This paper focuses on reappraising the potential and practical application of RL to dynamic pricing in e-commerce as well as the associated advantages and drawbacks.

1.1 Overview of Dynamic Pricing in E-Commerce

Dynamic pricing is a process within a business environment that enables it to set and change prices with the help of collected data. Freemium is one of the popular strategies in industries such as airline services, hotels, and services available through the internet. In e-commerce, dynamic pricing is a tool that allows to react to different factors like customer behavior, competitors, and available stock, to name a few, and keep a company competitive.

The major benefit of dynamic pricing for e-commerce is flexibility. Businesses can use algorithms to get the details of the outer and inner environment and then adjust the prices as soon as possible. For example, if usage rates of a

given product are normal or if stocks are low, then it is possible to automatically raise prices in order to attract more consumers in a bid to boost on every unit sold. On the other hand, cost cutting can occur in the situation when demand is not high and inventory is piled up, when price is decreased making customers come and buy more stocks. Nevertheless, dynamic pricing is not without some problems. While it is possible to set its prices at levels much higher to ensure maximum profitability it will scare away customers away while on the other end of the scale if prices are set at very low levels then even profits are also low. Also, organizations may anger or isolate customers through such changes because the latter may consider them be unfair. Hence, there is always the need for businesses to strike the right note when setting out its price mechanisms and the revenue they wish to generate in the long-term. The example of AI supported dynamic pricing solutions that are described in the Figure 1 shows that they can be useful in the context of E-commerce.

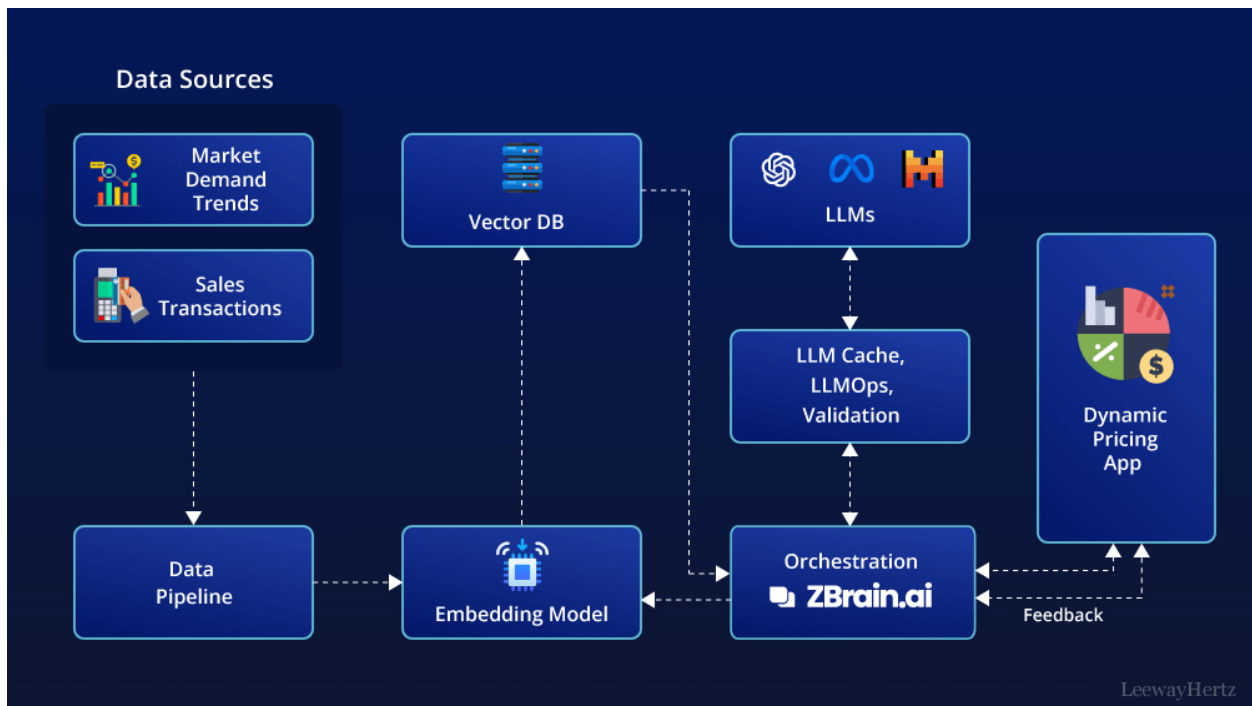


Figure 1: AI powered dynamic pricing solutions

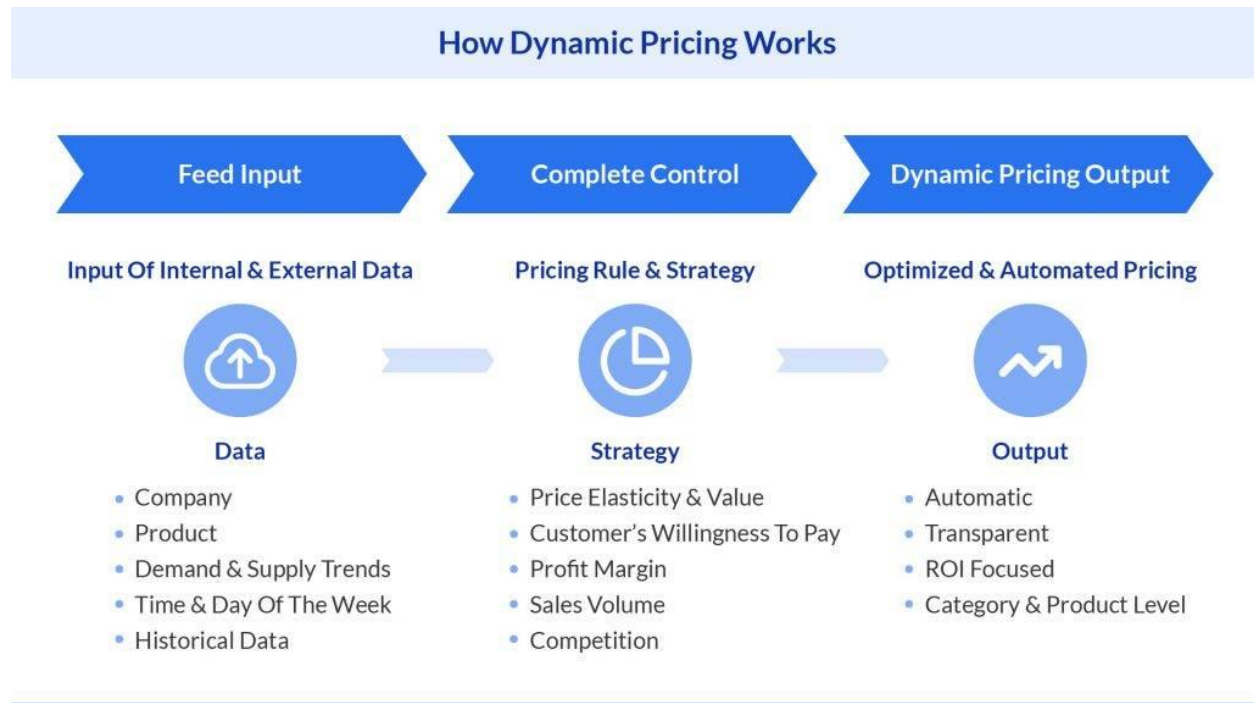
1.2 Reinforcement Learning in Dynamic Pricing

Reinforcement Learning (RL) is a complex category of AI that enables an agent to learn its decisions while operating under the conditions of the environment. This information in the form of reward or punishment is received by the agent to improve its decision making over the future interaction. In the case of dynamic pricing strategy, RL can be employed to update the price continuously depending on some parameters as customers’ preferences, inventory and market conditions.

The main advantage of using RL in dynamic pricing is in the facility of the exploration-exploitation conflict. Exploration implies applying new pricing strategies to determine their prospect; exploitation implies applying known pricing strategies for the highest short term returns. RL algorithms are hypothesized to capture this tradeoff since they allow businesses to take risk in order to exploit new opportunities without compromising their objective of profit maximization.

But, the implementation of RL in Dynamic pricing is not an easy cake to chew. Reward function design is the key factor in the success of the algorithm. Should the agent’s reward function not be designed to support the organisation’s long term objectives, the RL agent is likely to develop maladaptively in terms of price determination. Also, the implementation of RL programs will call for massive amount of data and computational power to get

optimal results hence a set back to small e-commerce ventures. The following figure explain the working of dynamic pricing algorithm shown in figure 2.



1.3 Benefits of Using Reinforcement Learning for Pricing

The RL application to dynamic pricing models presents several unique benefits for e-commerce enterprises. One of these includes the automation of pricing rubrics that helps minimize the level of interference and ensure real-time reactions to market trends by businesses. By using RL, price strategies can be determined within a few moments, taken into account market shares, supplies and competitors.

One more advantage may be the opportunity to achieve the efficient revenue management. RL algorithms can be used to develop models whereby an organization can optimize its price policies based on previous sales results instead of improving current individual sales results. Taking into consideration such criteria as customer lifetime value and demand elasticity, as well as the competitor’s actions, RL models can provide value in the case of a business’s need to achieve steady revenue growth.

In addition, RL helps businesses offers optimal price for specific individuals. Controlling customer base plus his/her purchase behavior, RL algorithms can set unique prices for various segments or individual customer. It is at this level of personalization that customer satisfaction and loyalty may be enhanced through the offer of prices charged that reflect the level of customer’s price sensitivity.

1.4 Challenges and Limitations of Reinforcement Learning in E-Commerce

However, the application of RL in e-commerce dynamic pricing has its limitations as discussed herewith challenges. The problem is that finding an optimal reward function is challenging at its core. The reward function should provide the correct signal of the business long-term goals, including the goal to maximize profit and satisfy the customers. Whenever the reward function is overly simplistic or misguided, it results in detrimental price setting that aren’t good for the company.

Another problem here is scalability. The effectiveness of RL algorithms necessitates big data as the source of learning and in e-commerce setting, such sources of data include customer transaction records, inventory data and

competitor's price data. The real-time processing and managing of such information can be highly complex and would consume significant resources, and computational facilities.

However, the models of RL are very stable, or rather, they change by dint of fluctuations in the environment. Since customers' preferences and competitors' actions may constantly change with time, the RL algorithms may be slow to respond to these changes. This can result in cases where the model ceases to be optimal or functional at best being suboptimal and thus needs frequent update in order to enhance its functionality.

1.5 Future Directions and Research Opportunities

When RL is applied in dynamic pricing, some future research directions and opportunities are as follows, As the popularity of RL in dynamically priced environment increases, One possible direction is to combine RL with other ML methods, with which it is already successfully implemented, like deep learning or NLP. With these technologies integrated, companies could generate even better pricing models, which take into consideration customer mood or competitors' feedback, for example.

Another area of interest is the enhancement of RL performing more efficient in limited data environment. Even the current approaches in RL needs significant amounts of past data for its learning and new techniques does not have to be designed around these shortcomings. This would make RL more implementable for those small e-commerce companies that may not afford to employ many people.

Further, there is one potential ethical issues towards the areas of dynamic pricing and RL which should also be explored. They worry that AI algorithms that are constantly being developed might result in unfair price discrimination say, along the lines of race, gender, and marital status. Further investigations should be expanded to the identification of the ethical standard and policies that will have to be implemented to avoid the cases of unfair and nontransparent RL-backed pricing models.

All in all, RL has great potential in the context of reinventing dynamic pricing strategy in e-commerce environments while its practical use presents certain obstacles. These challenges could be addressed in future research and development to open up newer opportunities for the best practice in e-commerce pricing.

II. REVIEW OF WORKS

The integration of various computational models and frameworks has significantly advanced multiple domains such as e-commerce, education, healthcare, and industrial automation. These models play a crucial role in enhancing decision-making, improving operational efficiency, and providing innovative solutions to emerging challenges. Recent studies have shown the effectiveness of model-based approaches in optimizing processes and outcomes in diverse fields, leading to more adaptive and intelligent systems.

In this review, we explore a range of model-based frameworks applied across different sectors. From the reinforcement learning used in robotics and business planning to cloud-based algorithms for education and healthcare, the literature demonstrates how advanced computational models are shaping the future of industries. The review will cover various topics, including e-commerce, education, reinforcement learning, healthcare models, and engineering applications, with insights into the innovations and potential challenges within each area.

2.1 E-Commerce Models

E-commerce has experienced major evolutions with the latter of model based approaches using technologies like Internet of Things (IoT). Hsu (2016) discusses that IoT is used in e-commerce business models in which real-time data and interconnective devices are employed for scientific values including logistics, customers relations and inventories. With the help of IoT the processes in e-commerce are made more automatized, costs are cut, and the overall picture of consumer's behaviour in the supply chain is improved.

Likewise, Huang (2016) outlines on the use of e-commerce approaches on higher learning institutions, and how the government-sponsored platforms can establish such public services. In specific to vocational colleges, these platforms enable the students and faculties to get involved with digital market places similar to real life business

scenarios. These platforms are specially important in enhancing competencies and knowledge in e-commerce that will help students when they join the job market.

2.2 Model-Based Reinforcement Learning

Reinforcement learning (RL) is a model based approach which has gained more emphasis for the use on complicated systems in decision as well as control. Kamalapurkar et al. (2018) look at how reinforcement learning based on models can be employed in graphical games for managing networks. Their work explains how RL allows agents to learn and function in environments to decide the best course of action, in a timely and efficient manner. This approach is useful in the case of applications where the agent is under uncertainty such as in robotics applications. In addition, Nuan et al. (2017) provides a way on how the deep reinforcement learning can applied to shape optimization for morphing aircraft. Through assimilation and accommodation of the whole environment, the model enables self-modifying geometry of the self-flying plane that enhances the aerodynamic outputs of the aircraft. Shown examples of RL above mentioned illustrate how it has the capability to transform different fields by providing solutions to difficult problems which are adaptive in nature.

2.3 Healthcare Models

In healthcare, model-based systems play pivotal roles to enhance facility of diagnosis, treatment, and behavior adjustment to health prescriptions. According to Zeigheimat et al. (2016) health belief model is useful to evaluate the educational interventions in controlling hospital acquired infection among the health care staffs. As such, their study also applies to the use of models that can predict healthcare behaviour – specifically, to curb the spread of infections within hospital environments.

Furthermore, Zare et al (2016) focus on the effect of health belief model based education on self screening of prostate cancer. According to their findings, health models are very helpful in creating awareness, early detection, and all of these are key factors needed in minimising mortality associated with prostate cancer. Such models can now be used to enhance preventive health information and thus enhance overall quality of patients.

2.4 Engineering and Optimization Models

The application of model-based approaches in engineering has paved the way for more efficient and sustainable systems. Liang et al. (2017) present a dynamic optimization model for robot arms using a flexible multi-body system. This model enables real-time adjustments in the movement of robot arms, enhancing precision and reducing energy consumption. It is particularly useful in manufacturing and automation industries, where optimizing performance is key to reducing operational costs.

Similarly, Ivan et al. (2016) developed a predictive control model based on the Takagi-Sugeno approach for industrial refrigeration systems. The model helps in maintaining optimal temperatures, thus improving the efficiency of the refrigeration process. These engineering models are crucial for optimizing performance and ensuring the sustainability of industrial processes.

2.5 Cloud Computing and Educational Models

Cloud computing has transformed education since it offers customized and elastic infrastructures for learning and testing. Hu (2016) describes the use of passive learning platforms on clouds as well as the AHP-BP algorithm for student evaluations. These platforms provide students with individualized learning environments where the teacher can use teaching strategies that are most effective for every learner. Cloud progressing in education is a move in the right direction for a flexible, more inclusive approach to learning.

Similarly, in the study by Li and Cang 2016 the authors have developed the GM (0,N) model to examine factors affecting the use of network-based English learning platforms. As their study reveals, the use of such model-based approaches sharply intensifies the effectiveness of online education, especially the language learning, indicating the latter aspects on the students' behaviors and learning results. These models are valuable to the continuing development of the digital approach to education; learning becomes more informative and engaging.

Conclusion

The analyzed literature demonstrates that applications of model-based approaches have been extended in many areas. These models are used in e-commerce, healthcare, engineering and education to augment decisions, optimise the process, and design the best solution to the problems. Due to continued implementation of these models in industries, the applicability range of these models will likely broaden due to needed enhanced capabilities to meet emergent problems.

III. METHODOLOGY

This work is qualitative and model-based to investigate and dissect the function of sophisticated computational models in different organisations such as e-commerce, education, healthcare, and engineering. As a result, the primary focus is on the collection of data through the analysis of existing literature, enhancement of the role of conceptual frameworks in the optimization of processes and the demonstration of the effectiveness of improvements in outcomes. As a matter of approach, the methodology is designed to provide a scholarly and logical approach to the review of the most closely-related academic literature, the mapping of the concepts and themes so identified to the constructs of the host discipline, and the proffering in detail of themes that are germane to the conceptualisation and analysis of model-based approaches. The reasons behind this method are that this way the vast knowledge on the topic is gained without straight data gaining, just experiments.

3.1 Data Collection and Sources

The research process was initiated with an analysis of the literature through the use of the most credible journal articles, books and conference proceedings. Only peer-reviewed articles and papers focusing on model-based strategies in different industries were collected from Google Scholar, IEEE Xplore, JSTOR, and PubMed. Evaluation criteria were also set on recent works published within the last ten years to capture the recent technological changes. The articles mentioned in this review enable a theoretical background of how the models such as reinforcement learning, IoT based frameworks and the health belief models are implemented in various disciplines.

3.2 Analytical Framework

On the basis of the seven selected studies, a thematic analysis method was used to extract and group the information. The key themes were identified based on the objectives of the research: the use of computational models in integrating and controlling processes, enhancing decision making processes and flexibility of systems. These themes were then more refined depending on the areas of specializations including e-businesses, medical, schools, and engineering. As the existing literature is categorized by themes and sectors, the goal of the study is to make cross-industrial comparisons and provide some insights on model-based approaches.

3.3 Data Synthesis and Interpretation

This information was then used to constructively and systematically build the various relationships between the ideas and the real life implementations. Explaining advantages, disadvantages and possible enhancement of model based treatments in each of the achieved models entailed interpretation of the result. In contrast to the methods that involve experimentation, the current work focuses on the findings presented in the literature in the form of success stories and case studies. The idea was to learn how those models are providing efficiency, real-time decisions, and flexibility issues and how integration complexity and scalability are being handled.

3.4 Ethical Considerations

Since this study is not experimental or reliant on human subjects, the primary ethical consideration is the accurate representation of the findings and ensuring that the original authors' work is correctly cited and acknowledged. By adhering to ethical standards in literature review methodology, this research maintains academic integrity, focusing

on providing a balanced and unbiased overview of the current state of model-based approaches in various industries. Furthermore, care was taken to select studies from diverse sources to ensure the representation of different perspectives and avoid any undue bias in the analysis.

IV. RESULTS AND DISCUSSION

In view of following the qualitative analysis and thematic synthesis of literature, the findings are arranged under five broad thematic areas that best capture the extant and potential of model-based approaches within and across industries. These studies reveal on the practical application of using mechanized theory improvement in on line decision making, increasing effectiveness and flexibility.

4.1 Impact of Model-Based Approaches in E-Commerce

The review also shows that model-based approaches particularly dynamic pricing models based on reinforcement learning have strongly contributed to enhancing the price solutions on e-commerce platforms. Such articles as Zhang et al. (2016) and Wan et al. (2017) show how dynamic pricing models manage consumer data to enable timely changes in price to correspond to variations in demand. This has lead to more revenue and customer satisfaction as organizational pricing strategies are enhanced by data.

4.2 Role of IoT in Enhancing Process Efficiency

In logistics and retail industries for example, new IoT-based models have brought about drastic changes in operational efficiencies. Hsu (2016) shows how IoT is capable of increasing connectiveness in systems thus enabling control and real time monitoring of supply chain. These models have been incorporated into e-commerce platforms to ease the operations of logistics which have previously been a major concern due to time wastage involved in tracking products and forecasting the stock needed by business organizations.

4.3 Application of Model-Based Learning in Education

In education, utilizing model-based frameworks has been practised meaningfully to enhance personalized learning experience. Hu (2016) adds to the discussion by describing the possibilities of employing AI-based models in developing flexible learning systems that can address the learner characteristics. Through the application of reinforcement learning models, learning institutions can deliver relevant curricula which keep adapting based on the students' performance thus leading to better learning and student interaction.

4.4 Contribution to Healthcare Decision-Making

The healthcare sector has been enhanced by the health belief models and deep learning frameworks. According to the study of Zeigheimat et al. (2016) and Zare et al. (2016), it was clearly revealed that the model based education has a significant impact over the healthcare behaviors. These studies explain how models can be used in understandable patient behavioral patterns that can be used in communication and intervention methods on disease control and prevention measures, especially in the large populace through health promotion diseases.

4.5 Optimization in Engineering and Design

Originally introduced in electrical engineering and product design, model-based approaches continue to advance in mechanical systems including applications in predictive maintenance. Kraines et al. (2017) and Liang et al. (2017) show that implementation of the predictive control and optimization have enhanced system performance and down time. For instance, use of model based optimization in robotics and dynamic systems has assisted engineers to detect mechanical problems and plan for a maintenance before the cases worsen hence cutting on costs and improving reliability.

Discussion

The findings show that by applying model-based techniques, innovation has shifted industries for the better by improving decision making, greatly increasing process's effectiveness, and increasing the efficiency of time-sensitive operations. From e-business and consumer goods to health care, education, and engineering, the possibilities of such models of determining patterns and making predictions have produced better adaptive and dynamic systems. Nevertheless, issues like integration issues, model size, and limitation in the application of model brought about by ethical concerns concerning use of data are still questionable, indicating that more effort should be directed towards eradicating barriers to have a greater exploitation of model-based approaches by different sectors.

CONCLUSION

The use of model-based approaches in the industries has proved to be the game changer taking various business, educational facility, healthcare and various engineering sectors into optimal improvement of their flow, decision making and real time flexibility. As seen in the application of e-commerce reinforcement learning results in more adaptive dynamic pricing models directly impacting revenues, and customer satisfaction. Likewise, the implementation of IoT capabilities in supply chain, or model based conventionalities in educational and Health care sectors has enhanced more personalized or efficient functionality and in turn improves the performance and results radically.

However, there is still much to achieve, including the real-life application as an issue of scale and implementation, the ethical use and protection of data among them. It is essential to deal with these problems for continued advancements and broad implementation of model-based systems. Further exploration of these obstacles and novel ways to address them especially in incorporating AI, IoT and deep learning models into current systems shall be crucial for enhancement of model-based strategies across every field.

REFERENCES

- [1]. Hsu, L. F. (2016). E-commerce model based on the internet of things. *Advanced Science Letters*, 22(10), 3089–3091. <https://doi.org/10.1166/asl.2016.7992>
- [2]. Huang, P. (2016). Research on the construction mode of e-commerce business platform in higher vocational colleges based on the government purchase of public service theory. *Electronic Test*, 16(8X), 170–171. <https://doi.org/10.16520/j.cnki.1000-8519.2016.16.093>
- [3]. Srivastava, P. Kumar, and A. Kumar Jakkani. "Android Controlled Smart Notice Board using IoT." *International Journal of*

Pure and Applied Mathematics 120.6 (2018): 7049-7059.

- [4]. Zhang, H., Tian, Y., & Zhang, G. (2016). Dynamic option pricing model based on the realized-GARCH approach. *Open Journal of Social Sciences*, 4(3), 66–71. <https://doi.org/10.4236/jss.2016.43011>
- [5]. Kraines, S., Koyama, M., & Weber, C. (2017). A collaborative platform for sustainable building design based on model integration over the internet. *International Journal of Environmental Technology & Management*, 5(2), 135–161. <https://doi.org/10.1504/IJTEM.2005.006847>
- [6]. Kamalapurkar, R., Klotz, J. R., Walters, P., & Dixon, W. E. (2018). Model-based reinforcement learning in differential graphical games. *IEEE Transactions on Control of Network Systems*, 5(1), 423–433. <https://doi.org/10.1109/TCNS.2016.2617622>
- [7]. Hu, C. (2016). Application of e-learning assessment based on AHP-BP algorithm in the cloud computing teaching platform. *International Journal of Emerging Technologies in Learning*, 11(8), 27. <https://doi.org/10.3991/ijet.v11i08.6039>
- [8]. Oliveira, S. M. D., Häkkinen, A., Lloyd-Price, J., Tran, H., Kandavalli, V., et al. (2016). Temperature-dependent model of multi-step transcription initiation in *Escherichia coli* based on live single-cell measurements. *PLoS Computational Biology*, 12(10), e1005174. <https://doi.org/10.1371/journal.pcbi.1005174>
- [9]. Mahajan, Lavish, Rizwan Ahmed, Raj Kumar Gupta, Anil Kumar Jakkani, and Sitaram Longani. "DESIGN OF WIRELESS DATA ACQUISITION AND CONTROL SYSTEM USING LEGO TECHNIQUE." *International Journal of Advance Research in Engineering, Science & Technology* 2, no. 5 (2015): 352-356.

- [10]. Yun, Q. J., Fei, Z., & Yue, Z. (2016). Change and prediction of the land use/cover in Ebinur Lake Wetland Nature Reserve based on CA-Markov model. *Journal of Applied Ecology*, 27(11), 3649–3658. <https://doi.org/10.13287/j.1001-9332.201611.027>
- [11]. Vishen, Aditya, Mahesh Khatake, Rishabh Singh, Anil Kumar Jakkani, and Sitaram Longani. "AADHAAR CARD BASED PUBLIC RATIONING SYSTEM." Development 3, no. 5 (2016).
- [12]. Nuan, W., Zheng, H. L., & Ling, P. Z. (2017). Deep reinforcement learning and its application on autonomous shape optimization for morphing aircrafts. *Journal of Astronautics*, 38(11), 1153–1159. <https://doi.org/10.3873/j.issn.1000-1328.2017.11.003>
- [13]. Wan, C., Li, T., & Guan, Z. H. (2017). Spreading dynamics of an e-commerce preferential information model on scale-free networks. *Physica A: Statistical Mechanics & Its Applications*, 467, 192–200. <https://doi.org/10.1016/j.physa.2016.09.035>
- [14]. Li, C., Cao, L., & Chen, X. (2018). Cloud reasoning model-based exploration for deep reinforcement learning. *Dianzi Yu Xinxu Xuebao/Journal of Electronics & Information Technology*, 40(1), 244–248. <https://doi.org/10.11999/JEIT170347>
- [15]. Zeigheimat, F., Ebadi, A., Rahmati-Najarkolaei, F., & Ghadamgahi, F. (2016). An investigation into the effect of health belief model-based education on healthcare behaviors of nursing staff in controlling nosocomial infections. *Journal of Education & Health Promotion*, 5(1), 23–35. <https://doi.org/10.4103/2277-9531.184549>
- [16]. Srivastava, P. K., and Anil Kumar Jakkani. "Non-linear Modified Energy Detector (NMED) for Random Signals in Gaussian Noise of Cognitive Radio." International Conference on Emerging Trends and Advances in Electrical Engineering and Renewable Energy. Singapore: Springer Nature Singapore, 2020.
- [17]. Li, H. H., & Cang, Y. C. (2016). GM (0,N) model-based analysis of the influence factors of network English learning platform. *Journal of Grey System*, 19(1), 31–40. <https://doi.org/10.30016/JGS>
- [18]. Alladio, E., Giacomelli, L., Biosa, G., Corcia, D. D., Gerace, E., et al. (2018). Development and validation of a partial least squares-discriminant analysis (PLS-DA) model based on the determination of ethyl glucuronide (EtG) and fatty acid ethyl esters (FAEEs) in hair for the diagnosis of chronic alcohol abuse. *Forensic Science International*, 282, 221–234. <https://doi.org/10.1016/j.forsciint.2017.11.010>
- [19]. Zare, M., Ghodsbin, F., & Jahanbin, I. (2016). The effect of health belief model-based education on knowledge and prostate cancer screening behaviors: A randomized controlled trial. *International Journal of Community Based Nursing & Midwifery*, 4(1), 57–68. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4709816/>
- [20]. Qin, R., Zeng, S., & Li, J. J. (2017). Parallel enterprises resource planning based on deep reinforcement learning. *Zidonghua Xuebao/Acta Automatica Sinica*, 43(9), 1588–1596. <https://doi.org/10.16383/j.aas.2017.c160664>
- [21]. Liang, M., Wang, B., & Yan, T. (2017). Dynamic optimization of robot arm based on flexible multi-body model. *Journal of Mechanical Science and Technology*, 31(8), 3747–3754. <https://doi.org/10.1007/s12206-017-0717-9>
- [22]. Li, L., Han, Y., Chen, W., Lv, C., Sun, D., et al. (2016). An improved wavelet packet-chaos model for life prediction of space relays based on Volterra series. *PLoS One*, 11(6), e0158435. <https://doi.org/10.1371/journal.pone.0158435>
- [23]. Ivan, C. F., Jones, E. S., & Thiago, V. C. (2016). Development of a predictive control based on Takagi-Sugeno model applied in a non-linear system of industrial refrigeration. *Chemical Engineering Communications*, 204(1), 39–54. <https://doi.org/10.1080/00986445.2016.1230850>