Pakistan Journal of Engineering Technology and Science (PJETS)
Volume 9, No 2, 2021

DIVERSITY AND UTILIZATION OF DYNAMIC PROGRAMMING (DP): A BRIEF OVERVIEW

[1] Maryam Younus, [2]Iqra Rehman
[1]Trade development of Pakistan, [2]Ziauddin University, Karachi

***Abstract*- "Dynamic programming" is a popular technique for handling an extensive range of Problems with sequential decision-making in the context of unpredictability. It permits us to calculate optimal choice rules, which identify the most likely decision in every given case. This article evaluates DP's evolution and compares because of the paucity of applications in the real world in different field like finance, operations research, economics, engineering, and artificial intelligence (AI) to help businesses and individuals make better decisions. The complexity of statistically modeling many real world choice concerns, as well as the fuzziness of many real-world decision issues, are important hurdles to broad application of DP in practical situations. Despite this, this review research found a number of successful experiments, and it was decided that DP provides considerable assurance for better decision making. The scientifically untenable concept of unconstrained rationality is challenged, as are the challenging choice issues that people encounter on a daily basis. Additionally, because of the sequential decision-making and simplicity of managing non-linear goal roles and constraints, it is considered a good approach for optimum operation. Although, owing to the complexity of the 'curse of dimensionality,' applying DP to significant and multi-directional situations is not very promising. Some of the algorithms developed to solve this problem for DP include incremental DP, discrete differential DP, DP with consecutive approximation, and incremental DP with successive approximation. Furthermore, in each of these instances, selecting a starting trial route, obtaining an optimal solution and the number of iterations necessary for convergence are all hard to enforce.**

Keywords: Algorithm, dynamic programming, optimization, artificial intelligence, bounded rationality, computational complexity.

I. Introduction

Since its inception in the mid-nineteenth century by "Richard Bellman," dynamic programming (DP) has been successfully applied to a wide range of issues in a variety of areas [1, 2]. One of the most important features of DP is potential to adjust for a structure's dynamics, and it is usually utilized by operations investigators to address problems existence decisions. DP can also handle a wide range of cost and/or reward functions, unlike the bulk of optimization approaches. Because of its versatility, it is envisaged that DP will be employed in a variety of fields, including artificial intelligence, control, economics, and operational research. DP, on the other hand, has several disadvantages. The capacity of a dynamic program grows swiftly in proportion to the problem's

[1]maryam.younus@tdap.gov.com,
[2]iqrarehman091@gmail.com

complexity. This is known as the "curse of dimensionality," and it has been the most difficult aspect of applying DP techniques to real-world problems. Investigators have advocated a variety of estimation techniques, including state aggregation and value function evaluation, to solve large dynamic problems, taking into account the computational complexity that result from the curse of dimensionality [3].

Richard Bellman used the term DP in 1950 to describe a recursive approach for determining optimum strategies and decision criteria for a broad variety of dynamical, successive decision making scenarios including ambiguity[4]. The invention of differential equations (DP) use of mathematical application as a principal indicator of mathematical modeling revolutionized the way we understand economic principles. It is undoubtedly the most essential tool in game theory, macro and micro economics [5, 6]. Many combinatorial optimization issues are computationally intractable. In practice, however, we are typically happy with reasonably excellent results, and approximation algorithms are crucial in this regard. There are a number of tools that may be used to create approximation algorithms. The greedy technique, which directly creates approximate solutions by gradually calculating the values of variables based on some local knowledge, is likely the most prevalent.[7].

II. DISCUSSION ON THE UTILIZATION OF DYNAMIC PROGRAMMING

Dynamic programming (DP) is the process which can easily be utilized to solve problems related to scheduling. Many researches executed the dynamic programming in the scheduling problems. Other then scheduling exercises [8]offered process of heuristic solution by implementing dynamic programming to determine the employment of out-sourcing as a mean to overcome the disruptions related to the supply chain in manufacture scheduling for unexpected consumer orders. The while a study conducted by [9]in this study author established a program to schedule surgical procedure at the hospital to reduced time of waiting, overtime in operating room and bed availability in ward. For that dynamic program was used to achieve the required output.[10] A self-styled polynomial DP has been putted in to operation for determining the outstanding dates and costs required in the allocation of resources delivery of batch to control the delay in jobs.

Furthermore[11] planned a schedule for aircraft landing on a single run way through dynamic programming.[12]an exact algorithm was proposed by the author to discover the optimal sequences for a shop scheduling issue depend upon DP.[13]in this study author developed a model of stochastic DP to obtain optimization by a proposed schedule of aircraft replacement keeping variation in the market demand and aircraft status in the focus. Moreover[14]build up approximate dynamic programming (ADP) algorithms to solve stochastic project scheduling problems. In a study conducted by [15]build-up a schedule using adaptive DP to maximize the patients level of satisfaction which is dependent on uninterrupted meetings.[16]a new version of DP algorithm was offered for the solution of problems related to scheduling of tasks perform individually with uniform out-standing due date and to reduce unpunctuality weight of task.

Additionally, for proper management regarding technology replacement which is directly associated with proficiency can be managed via DP. It can be a major tool for solving the problems as stated in [17].

Moreover [18] The application of DP in E-grocery stores where the aim of utilization was to develop a method to control the demand of the online orders through the cost of delivery time. Meanwhile, another study[19]build up a model under DP for the process of coal mining investment related environmental decision making associated with the optimization of draft.[20] The research study planned a DP with new idea which made a tradeoff between cost for the draft and reliability. Also[21] implemented DP in creating a balanced assembly line to constrain optimal resources. Many of the researches used DP to solve stock related problems. For example[22]Applied multi stochastic DP to tackle stock replenishment problem in a reverse supply chain and [23] discovered the solution of a multi localities stochastic stock system through forward approximate DP[24]In this study authors initiated a model which was based on a DP for a limited scope of solo manufactured goods with doubtful likelihood division of demand. Moreover[25] recursion in DP was included as mixture of integer linear programming in stock related scheduling issues.

Difficulties in the knapsack, a number of instigators believed on the implementation of DP in addition. Furthermore in[26]study projected an algorithm based on DP for the knapsack issues with complex that generally applicable in Planning of manufacturing, [27] In the following study 2DP algorithms where the 1st one was projected for complexity of linearity on the quantity of items, whilst the 2nd one was used for complexity at the capacity of the knapsack. Furthermore[28]proposed a DP for packing knapsack with lowest amount of cost and optimal profit. Added; that utilization of DP in routing and transportation problems is very common and frequent. [29]

In this study authors proposed a model of DP was created and rum for a multi model transporter for reducing the transportation cost. [30] In this research, two different algorithms DP and ant colony have been merged to get optimized results in disaster condition in deployment of emergency material emergency via transportation.

Study done by [31]offered an approximate DP move towards to optimize time for handling and find out space to store in a coil warehouse. In the interim[32]put forward a markovian decision model and approximate DP to resolve vehicle routing problem for emissions minimization, Where[33] genetic algorithm and exact DP procedure was combined for green vehicle routing and scheduling problem. DP is used to deal with plantation as well. [34]illustrated the utilization to optimized model to replanting policy that deems CO2 emission and commercial advantages. In this research paper the best schedule was obtained for the best total cost of picking tea by using DP.

III. ALGEBRAIC DYNAMIC PROGRAMMING (ADP)

Exact solutions of many problems can be obtained through dynamic programming (DP) algorithms especially in biology computations, more over in sequence alignment, scoring of phylogenetic trees and hidden Markov models (HMMs). Evaluation of distribution of score, performing stochastic sampling and competitions for optimal solutions can be done via structurally analogous algorithms. As we can learn in ADP through a severe division of state space traversal, encoded as algebra, and rule of choice. The main component of the ADP is the application of yield examiners who work on the structures statistics, commonly ordered and string trees. The unaligned properties of computation such that; HMMs posterior probability, RNA folding (partition functions) which involves the two distinct combinations other than the algorithms related to intimate, recognized as in and outside recursion whilst the classical theory of AD sheltered only the inside recursions[35].

IV. DP PROBLEM APPROACHES

Practically all genuine DP issues must be solved numerically. conventional techniques that rely heavily on human input and programming, and machine learning and reinforcement learning algorithms that can discover optimal solutions via trial and error experimentation[36]. In the AI and DP research literatures, the term "learning" refers to two things: Learning the optimum decision criterion and problem paradigm, which includes the DM's incentive or objective utility and the conservation of momentum managing system parameters in the DP problem, but rather how decisions affect rewards and situations in the DP predicament. Learning the optimum decision criterion and issue paradigm, which includes the DM's reward or goal function and the conservation of momentum controlling system parameters in the DP issue, is less important than understanding how decisions effect rewards and situations in the DP predicament. The term adaptive oversight is used in the DP and manage literatures to describe situations in which the DM attempts to become skilled at the formation of the DP predicament while also attempting to make proper decision, in cases like the multi-armed bandit conundrum, this is likely to result in the typical tradeoff among exploration and exploitation [37].

According to the researches, the essential element and approximated solutions are determined before the decision rule is being used to make or propose judgments, and when decisions are taken, the algorithm updates its estimate of the problem structure and the ultimate decision rule. Several algorithms which are real time learning based have the benefit of not having precise utility functions for the fundamental inclinations, assumptions, and “laws of motion” that ensures the integrity of the basic problematic situation. An additional notable difference is either the learning is evaluated.

The presence of a professional DM whose conduct can be monitored and employed to train a decision rule, either through simple extrapolation approaches that understand preferences and laws of motion for state variables from scrutinized manners of specialist DMs are assumed in supervised learning. Un-supervised learning, such as RL, "comes into play" when examples of desired behavior are unavailable but instances of conduct may be scored based on some performance decisive factor[38].

It is used to find optimal decision rules in ‘games against nature’ and sub-game perfect equilibrium of dynamic multi-agent games, and competitive equilibrium in dynamic economic models. DP has enabled economists to formulate and solve a huge variety of problems involving sequential decision making under uncertainty, and as a result it is now widely regarded as the single most important tool in economics.[4]

V. DP APPLICATIONS TO IMPROVE DECISION MAKING

DP is only employed in a many real-world scenarios. It is reasonable to assume that the stakes for implementing profit-maximizing programs are relatively high; consequently early adopters of DP should be profitable, inventive entities that can generate the resources needed to solve tough decision. Nonetheless, regardless of the fact that It has not conducted a systematic investigation, several companies that are likely to implement DP look hesitant or unwilling to discuss it. Multi-period optimization is used in some cases, however it should not be considered DP[36].Additional issue that restricts the use of DP is that the target function that many organizations are optimizing is hazy and ambiguous. In economics, the default assumption by government companies is to maximize their market share. This is the expected trickle of future earnings reduced at a risk-adjusted discount factor. Conversely, a significant body of financial evidence on the disproportionate stock price volatility market prices poses serious reservations about what the firm's net worth is comparable to its fundamental value, which is the estimated present value of its future income flow. Even if all of the other incentive difficulties associated with running a business could be handled, it means that the aim function of an administrator should never longer be to maximize predicted discounted profits to the degree that stock market values include a strong and systematic noise component. The absence of contrivances and procedures to assess whether a DP-based decision solution should be developed or acquired creates enough extra income or profit to justify its adoption is a final obstacle to its deployment. There are very few examples of method validation conferred, but more rigorous systematic process potentially help to increase the integrity of decision based on dynamic programming aids and widen their range of real world implications. [36].

VI. NUMERICAL ASPECTS OF DYNAMIC PROGRAMMING

Dynamic programming that breakdown the way out to resolve hurdles recursively connected simpler set of sub-problems. This is taken from Bellman’s principle of optimality “An optimal policy has the property that whatever the initial state and the initial decision are, the remaining decisions must constitute an optimal policy with regards to the state resulting from the first decision.” [39]the perceptive is that using backward induction to solve a dynamic game generates an optimized decision rule that complies to Bellman's principle of optimality Backward induction is based on the optimality principle, which uses time as the indicator, but [40]Backward induction for dynamic games has been generalized to established state recursion. They described a problem-state ordering that formally expresses the perceptual conception of diamentiality. This figure demonstrates how to disintegrate the SDP into phases; this can be used as a backward induction course indication instead of the normal time indexing. While it is technically possible to recast and solve optimum decision rules for SDPs as statically, "approachable" optimum concerns, it is often significantly more efficient to solve them using DP, which decomposes the overall issue into a series of undersized, a lot more manageable sub-problems. DP emerged in the mid nineties as a consequence of a convergence of work on optimum hydropower reservoir operation, early statistical decision theory, optimal inventory control, and game theory at the same time that the first digital computers[49] were being developed [41].Despite the fact that the term programming conjures up images of computer programming, since computer systems were incapable of tackling most real DP challenges, much early work on DP was theoretical. In fields like operations research, resource management and engineering management of electricity grids and power generation, communications and network[46] routing, the utility and flexibility of DP for formulating and solving a wide range of problems and games of practical importance and relevance was quickly recognized [3].Dynamic games have been widely used in economics, where businesses and customers are supposed to be rational actors with optimum decision rules governing their behavior. As a result of Its application in the formulation of inferential and counterfactual strategy projections, In econometrics, there is an empirical evidence on numerical method and estimation of "dynamic structural models"[42].Because of the large number of SDP applications, There's also a desire for more powerful numerical techniques on digital computers to answer or estimate the services to major DP issues, which are developing at exponential rates owing to the digital revolution and countless technical improvements encapsulated in "Moore's Law." Many actual DP issues, on the other hand, might be huge in size or dimensions[43]. In DP issues when the DM is unknown, The method of Bayesian learning is used when the DM does not observe the true state or does not completely comprehend the law of motion driving the state variables, Bayesian learning is used, and one of the DP problem's state variables is the posterior distribution over these uncertain values. Unless the problem satisfies restrictive restrictions for the posterior to be a member of a conjugate family, it is an infinite dimensional state variable. Even if we approximate this posterior with a finite approximation, the result is a finite dimensional DP problem with a very high dimension.

The amount of potential values can be enormous yet in situations or games when there is a limit to the size of the state space. Chess has roughly 1050 potential board locations, whereas there are more than 10100 positions in the game of checkers. According to created the phrase "curse of dimensionality" to characterize the exponential growth in computer time required to tackle more concrete and specific DP problems, there's more than the number of atoms in the observable world

[39]. The researcher did not indicate if the constraint of dimensionality is a permanent "limit to science" or merely a source of concern that might have been solved with better techniques and speedier computers. In the following literature on knowledge based complexity in computer science, the "curse of dimensionality" is stated as the computing[47] of an explicit model that identifies by some mathematically related operations such as integrations. To find an accurate output, a vast quantity of data about the underlying function is necessary, yet real world computers and algorithms can only use a limited amount of data to find an optimal options [44].With this architecture, computer programmers were able to characterize a variety of mathematical issues connected to the curse of dimensionality, confirming that it is a basic "limit to science" that no algorithm, no matter how sophisticated, can evade. Any mathematical issue that is intractable and prone to the curse of dimensionality is described as such by computer programmers. In the worst-case computing expenditure of producing an approximation to the true solution, the number of continuous variables or dimensionality of the issue grows exponentially.

VII. EMPIRICAL DYNAMIC PROGRAMMINGAND THE IDENTIFICATION PROBLEM

The advancements in numerical DP paved the door for a burgeoning literature on empirical estimate and testing of SDPs and dynamic games. The existing knowledge on estimate of dynamic labor demand schedules in a linear quadratic framework began to condense around the end of the 1970s, at the same time as a number of publications appeared that gave diverse methodologies. To develop ancient discrete optimized algorithm DP is considered as a influential and common technique. To crack the numerous difficult problems related to computer vision like detection of curve, completion of contour, matching of stereo and alignment and matching of distort object can be solved by using DP algorithm. To breakdown the problem into sub problem is the key idea of DP like that; (I) provide a solution to the sub-problems, where the solution of the problem can be computed quickly for the main problem, and (II) recursively solution of the sub-problem can be done efficiently in term of each other. The significant characteristic of DP is that the way out of a sole sub-problem is repeatedly used for cracking numerous bigger sub-problems. In the DP algorithm the provided solution not further needed to be verified and there will not be needed of re-computations. This is the major benefit which differentiates DP algorithms from classical recursive algorithms. Comparable to shortest paths algorithms, DP relies upon optimal sub-structure property. That creates the possibility to solve sub-problem using solutions of smaller sub-problems.

A DP algorithm may be thought of as a way for filling up a table, with each table entry corresponding to one of the sub-problems we must solve. The DP algorithm iterates through table entries, calculating a value for the current item based on the values of previous entries. Often, a simple recursive equation describes the value of one entry in terms of the values of other entries, but calculating a value might be more difficult. [45].

VIII. FUZZY DYNAMIC PROGRAMMING

There is availability of fuzzy system literature in the context of verity of situations and several algorithms for their treatments, which occurs due to clustered data in fuzzy environment. As an extension of conventional DP Bellman introduced a model for fuzzy scenarios. Two models of fuzzy DP were initialized and switched into algorithms. Comparison of heuristics-based performance of algorithm was done. The usage of dynamic programming in data presented in clustered form is substantial way to resolve the issue.

Though, there is a brief discussion on the conception about the multi stage decision making in fuzzy environments as a preamble growth of the algorithm for cluster analyzation. For the modeling and optimization of any process in a fuzzy environment fuzzy DP is an effort to inoculate the theory of fuzzy sets. The DP based algorithm approaches steadiness considerably quicker as compared to the algorithms based on heuristic. Fuzzy DP is accurate for both the unenthusiastic as well as positive assessments. A main benefit of fuzzy DP which is not stated here is the possessions that the fuzzy cluster's optimal numbers can be find out through the algorithm via grouping procedure. Fuzzy DP considered as an efficient instrument for the construction of an algorithm that is particularly well matched for fuzzy data in clusters. Optimum and stability components of DP appear to have also been relocated to its fuzzy analog. The program is stress-free to write and implement. Additional, in the one directional description, striking computational problems are the typical characteristic of DP which were encountered with the execution of the algorithm [46].

VIII. CONCLUSION AND FUTURE RESEARCH DIRECTION

Dynamic programming (DP) is an exceptionally strong approach for handling a wide range of uncertain sequential decision problems. Indeed, it's difficult to imagine an issue that can't be expressed and solved with Dynamic programming. The discipline has been transformed by the adaptability and strength of DP, and it has offered a basic concept that has resulted in some of the most astounding AI successes. The complexity of using DP to design and answer the very multifaceted, ambiguous and depravedly described decision issues that entities and businesses come upon on an everyday basis is the primary grounds for its limited number of real-world implementations. Although DP has been quite efficient for academic modeling, articulating and addressing ultimate decision issues as mathematical problems has proven to be significantly more challenging. It is commonly understood that as computer power and algorithms improve, so does the range of real-world problems that DP can handle. Despite massive computer influence and decades of research that have provided a profusion of substitute clarification strategies for difficulties of dynamic programming, the number of known real-world utilizations of DP remains surprisingly limited even now.

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