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ADOPTING AI TECHNIQUES IN ROBOTIC FABRICATION IN ARCHITECTURE:
INTELLIGENT ROBOTIC BRICKLAYING USING REINFORCEMENT LEARNING ALGORITHMS

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
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BY

ALIREZA MAALI ESFANGAREH

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FOR
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ABSTRACT

ADOPTING AI TECHNIQUES IN ROBOTIC FABRICATION IN ARCHITECTURE:
INTELLIGENT ROBOTIC BRICKLAYING USING REINFORCEMENT LEARNING ALGORITHMS

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Today, the Fourth Industrial Revolution is taking place and changing many industries and manufacturing methods to fulfill the tremendous global demand for different products and services using every available technological development. Moreover, in the context of Industry 4.0, one of the most critical challenges of Cyber-Physical Production is to have not only economically efficient but also adaptive and flexible production methods under different circumstances. However, by a simple investigation of the architecture industry and especially the construction sites, it will be witnessed that the existing techniques are remarkably far from the standards of Industry 4.0.

Therefore, this research is going to investigate the potential of implementing artificial intelligence techniques into the existing robotic construction methods to propose a smarter and more flexible process of fabrication using robots. In this scope, reinforcement learning algorithms which are a sub-category of machine learning algorithms are utilized to train an industrial robotic arm in a set of simulations to perform unsupervised and automated bricklaying tasks. The feasibility of the proposed method is put to test by five case studies of different prototypes.

Consequently, The analysis of the results of the training simulations in these case studies demonstrates that applying reinforcement learning algorithms in robotic automated bricklaying methods can provide tools via intelligent agents to establish advantageous cyber-physical systems in the construction industry. This can establish a smart process of employing robots by architects and designers to pave the way for the architecture industry to cope with the emerging demands in the frame of Industry 4.0.

Keywords: Robotic Construction, Automated Bricklaying, Reinforcement Learning Algorithms, Cyber-physical Systems, Industry 4.0

ÖZ

MİMARİDE ROBOTİK İMALATTA YAPAY ZEKA TEKNİKLERİNİN UYGULANMASI: GÜÇLENDİRME ÖĞRENME ALGORİTMALARI KULLANARAK AKILLI ROBOTİK TUĞLA YAPMA

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Yüksek Lisans, Yapı Bilimleri, Mimarlık
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Bugün, Dördüncü Sanayi Devrimi gerçekleşiyor ve mevcut her teknolojik gelişmeyi kullanarak farklı ürün ve hizmetlere yönelik muazzam küresel talebi karşılamak için birçok endüstriyi ve üretim yöntemini değiştiriyor. Ayrıca, Endüstri 4.0 bağlamında Siber-Fiziksel Üretimin en kritik zorluklarından biri, sadece ekonomik olarak verimli değil, aynı zamanda farklı koşullar altında uyarlanabilir ve esnek üretim yöntemlerine sahip olmaktır. Ancak mimarlık endüstrisinin ve özellikle şantiyelerin basit bir incelemesi ile mevcut tekniklerin Endüstri 4.0 standartlarından oldukça uzak olduğu görülecektir.

Bu nedenle, bu araştırma, robotları kullanarak daha akıllı ve daha esnek bir üretim süreci önermek için yapay zeka tekniklerini mevcut robotik yapım yöntemlerine uygulama potansiyelini araştıracaktır. Bu kapsamda, makine öğrenmesi algoritmalarının bir alt kategorisi olan güçlendirme öğrenme algoritmaları, bir endüstriyel robotik kolun denetimsiz ve otomatik tuğla örme görevlerini yerine getirmek üzere bir dizi simülasyonda eğitilmesi için kullanılmaktadır. Önerilen yöntemin fizibilitesi, farklı prototiplerin beş vaka çalışmasıyla test edildi. Bu vaka

çalışmaları üzerindeki eğitim simülasyonlarının sonuçlarının analizi, robotik otomatik tuğla örme yöntemlerinde takviyeli öğrenme algoritmalarının uygulanmasının, inşaat sektöründe avantajlı siber-fiziksel sistemler oluşturmak için akıllı ajanlar aracılığıyla araçlar sağlayabileceğini göstermektedir. Bu, mimarlık endüstrisinin Endüstri 4.0 çerçevesinde ortaya çıkan taleplerle başa çıkmasının yolunu açmak için mimarlar ve tasarımcılar tarafından robotların kullanılmasına yönelik akıllı bir süreç oluşturabilir.

Anahtar Kelimeler: Robotik Konstrüksiyon, Otomatik Tuğla Örme, Güçlendirme Öğrenme Algoritmaları, Siber-Fiziksel Sistemler, Endüstri 4.0

Dedicated to all workers who have been struggling to construct and reshape our world.

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AEC ……………………………….... Architecture, Engineering, and Construction

AI ………………………………….. Artificial Intelligence

BIM …………………………………. Building Information Modeling

CAD …………………………………. Computer Aided Drawing

CAM ………………………………… Compute Aided Manufacturing

CC ……………………………………. Cloud Computing

CNC …………………………………. Computer Numerically Controlled

CPS ………………………………….. Cyber-Physical Systems

CS ……………………………………. Cyber Security

DP ……………………………………. Dynamic Programming

GA ……………………………………. Genetic Algorithms

I4.0 …………………………………… Industry 4.0

IoP …………………………………… Internet of People

IoS …………………………………… Internet of Services

IoT …………………………………… Internet of Things

MDP …………………………………. Markov Decision Process

ML …………………………………… Machine Learning

NN …………………………………… Neural Networks

RL ……………………………………. Reinforcement Learning

TD ……………………………………. Temporal Difference

CHAPTER 1

INTRODUCTION

Architecture is one of the oldest practices of mankind and one of the largest industries worldwide today. In each era, architectural design and construction have played important roles in different societies. Due to its importance, architecture has evolved and been subject to many changes and enhancements in terms of styles, materials, building methods, etc. throughout history to meet the demands and requirements of its own historical period.

Today, the Fourth Industrial Revolution is taking place and changing many industries and manufacturing methods to fulfill the tremendous global demand for different products and services using every available technological development. Moreover, in the context of Industry 4.0, one of the most critical challenges of Cyber-Physical Production is to have not only economically efficient but also adaptive and flexible production methods under different circumstances. However, by a simple investigation in architecture industry and especially the construction sites, it will be witnessed that the existing techniques and methods are remarkably far from the standards of Industry 4.0, the era that we are living in. By paving the way for implementing cutting edge technologies into various processes of this industry, we can make noticeable enhancements to make architecture one of those which are capable of coping with the emerging demands in the frame of Industry 4.0.

The German government, in 2011, have introduced to the world a new topic called Industrie 4.0, hypothesized as fourth industrial revolution. (Wagner et al., 2017) The ultimate goal of Industry 4.0 is to operate with an enhanced level of automatization to approach a higher stage of operational efficiency and productivity which integrates the virtual world to the physical world and brings computerization and connection into the traditional industry. (Lu, 2017)According to Alcacer and Cruz-Machado (2019), “I4.0 is a Cyber-Physical Systems (CPS) production, based on heterogeneous data and knowledge integration and it can be summed up as an interoperable manufacturing process, integrated, adapted, optimized, service-oriented which is correlated with algorithms, Big Data (BD) and high technologies such as the Internet of Things (IoT) and Services (IoS), Industrial Automation, Cybersecurity (CS), Cloud Computing (CC) or Intelligent Robotics.” (Alcácer & Cruz-Machado, 2019)

The studies on implementing elements of Industry 4.0 into architectural construction projects have demonstrated that the integration brings about considerable enhancements to this industry from many points of view. (Oesterreich & Teuteberg, 2016) These enhancements can be categorized and listed as below:

Cost savings: The automation of labor-intensive processes by employing robotics and automated workflows can result in reducing the cost of labor. (Bruemmer, 2016) Moreover, by use of embedded sensors, the automated tracking of equipment and material can assist to reduction in material costs. (Sardroud, 2012)

Time savings: Contemporary manufacturing concepts and technologies such as Prefabrication, Robotic Fabrication, and Additive Manufacturing increase the speed of building constructions remarkably compared to older methods. (Oesterreich & Teuteberg, 2016) (MHC, 2011)

On-time and on-budget delivery: The use of elements such as complex simulations or Building Information Modeling can be a profitable assistance to manage delivery time and keep projects low budget which used to be a challenging task in traditional construction projects. (Jones, 2016)

Improving quality: At any stage of design and construction process, using BIM and other simulations can discover and terminate errors. This has been proven to help to increase the quality of constructed buildings. (Allison, 2015) Additionally, analytics of Big Data will assist project managers to plan more persuasive and smart chain of decisions. (McMalcolm, 2015)

Improving communication and collaboration: As the number of participants in every construction project is considerably high, cloud and BIM platforms or other social media apps can enhance collaboration efficiently. (Merschbrock & Munkvold, 2015)

Improving safety: Several research on safety management demonstrates that safety is one of the most critical affairs in construction projects. The construction industry, because of its dangerous work environment is famous for its dramatically high rates of work accidents and injuries. (Chun et al., 2012) Subsequently, many different approaches have been introduced by researchers and practitioners to enhance construction safety, by virtual safety training (Guo et al., 2013), using risk maps for evading labor accidents or utilizing wearable technologies such as Smart Helmets Glasses. (Vahdatikhaki & Hammad, 2015)

Enhancing sustainability: The construction industry is responsible for excessive carbon dioxide emissions, energy consumption and producing immense amount of waste during its different processes. (Chou & Yeh, 2015) Several approaches have been proposed in order to handle these environmental problems for construction waste minimization (Yuan & Wang, 2014), for project emissions reduction through strategic project management (Tang et al., 2013) or to use BIM to produce design alternatives. (Davies & Sharp, 2014)

Considering this and with the aim of benefiting from some contemporary technologies in an ancient process of building, this research is going to investigate the potentials of implementing artificial intelligence (AI) techniques into existing robotic bricklaying methods to establish a smart process of employing robots by architects and designers. Artificial intelligence is a field of software engineering and technology that focuses on intelligent computer programs or algorithms (Kate et al., 2021). The goal of AI systems is for machines to be able to imitate human "cognitive" skills including reasoning and problem-solving in order to conduct tasks that are ordinarily performed by humans. AI tasks are carried out by storing and analyzing massive amounts of data with the aid of those algorithms (Manyika et al., 2013). Smart machines can be used for construction projects by harnessing robots that can undertake repetitive tasks that humans once performed, like as bricklaying. AI systems can also collect and organize data for engineers to use in project planning and implementation (Kingston, 2016).

Although there have been studies and implementations of robotics in architectural design and fabrication process in the last decades, the developed methods until today can be enhanced from many aspects so that architects and construction specialist can benefit from more intelligent and productive tools in both design and construction phases. One of these many aspects, which can be made advantage of in construction using robotics is adopting recent advancements in artificial intelligence methods that are being developed and used in other industries.

Investigating through these methods, in the scope of this research, several artificial intelligence algorithms have been studied and tested to achieve the most feasible and functional integration of the algorithms and existing robotic fabrication techniques. Among these algorithms were evolutionary metaheuristic optimization methods and Machine Learning (ML) algorithms such as Genetic Algorithms (GA), Deep Learning methods, Neural Network algorithms (NN), and Reinforcement Learning (RL) Algorithms. In the next step, the most applicable set of these algorithms which are also considered as one of the most advanced artificial intelligence algorithms have been selected as a tool to approach the aims of this research. Reinforcement Learning algorithms, which function based on a simulation of an environment and an intelligent agent being trained to perform certain objectives, are chosen for training our intelligent method of employing robots in architectural fabrication process. More details on the features and capabilities of this sort of algorithms and the logic behind preferring them to other methods in this research have been thoroughly discussed in the next chapters.

To test and prove the hypothesis of this research which is to state that by integration of latest AI advancements to the existing robotic construction methods, we can train robots as intelligent agents to perform human labor tasks on construction sites, a research design has been conducted that consists of different steps. This simulation-based research is following a flow from designing primitive prototypes to training a robotic arm as the intelligent agent to construct the prototypes by bricklaying. Several platforms and tools are combined in this research design to achieve the objectives of this research which will be introduced and discussed in the related chapters.

CHAPTER 2

LITERATURE REVIEW

2.1 Construction, Industry4.0, and Its Elements

In the early years of this century, the first commercial solutions to one of the most critical difficulties in construction informatics – structured information sharing on construction products – developed. Building Information Modeling (BIM) software began to take the place of CAD and drafting tools (CADD). Because many ICT solutions in the construction industry process data in some manner, BIM has become a core concept and a focus of numerous research efforts. (Eastman et al., 2011). The drawn line was overtaken by a digital object that can also be understood by a computer after decades of being the basic information unit for transmitting information in engineering (in the building context). Commercial software now commonly supports structured information work, and it is becoming normal practice in design and construction; countries are beginning to establish statutory requirements for its usage. (EU BIM Task Group, 2017) This evolution followed the same pattern as that of all other sectors and professions. It all started with the advent of generic software (such as word processing, spreadsheets, and, in our case, CAD software) that can be used for a variety of purposes and is not restricted to a single application. To enable well-defined repetitive operations, enterprise information systems powered by relational databases and higher-level frameworks arose shortly after. (Romero & Vernadat, 2016). A human, on the other hand, has served as a link between information systems and physical events. Human participation was used to enter most information into information systems. Human activity, based on digital analysis, makes a difference in the real world. However, a number of technologies, the most of which fall under the umbrella of the "Internet of Everything," have begun to change that. It meant that the "real" world was beginning to be furnished with sensors and controls that would enable a human-free bridge between the physical and digital worlds. The setting was set for something unusual, and Industry 4.0 was accountable for it. (Klinc & Turk, 2019)

The pass to evolution of Industry 4.0 from Industry 1.0 to Industry 3.0 can be summarized as follows:

• Industry 1.0 - mechanization. It all started with the development of water-based energy generation and steam power as a supply of (mechanical) energy. This shift from agricultural and rural to European industrial civilization happened in the late 1800s and was based on three natural resources: coal, iron, and rivers (Balasingham, 2016). (Sharman, 2017). Not only did steam engines have an impact on heavy industries such as iron and textiles, but also on transportation, communication, and other commercial sectors (Rifkin, 2016). Nonetheless, labor was the most significant resource — albeit one helped by machines (Von Tunzelmann, 2003).

• Industry 2.0 - electrification. According to Rifkin (2016), around the start of the twentieth century, electricity (rather than oil and coal) developed as a primary source of energy, setting the framework for the second industrial revolution. This enabled electrically powered commodity mass manufacturing, often known as serial production (Industrie 4.0 Working Group, 2013). Production processes were relatively easy, leading in high labor-assisted machinery efficiency and the establishment of a social middle class with financial stability (von Tunzelmann, 2003). (Balasingham, 2016).

• Industry 3.0 - automation. Even though the first computers were constructed in the 1930s, it took decades for them to become more powerful and dependable while remaining small and controllable (Sharman, 2018). The advent of computerization into existing serial manufacturing, digitally assisted design, and numerically controlled equipment marked the tipping point in the 1970s. The digital revolution was given its name because computers played such an important part in the shift from an industrial to an information society (Balasingham, 2016). Hence, it made it possible to automate manufacturing processes using IoT (Preuveneers & Ilie-Zudor, 2017). Industry 4.0 was introduced in Germany at the beginning of this decade as a strategic response to the rivalry brought on by Asia's fast industrialisation. The European Union finally adopted it as an umbrella term for efforts aimed at upgrading European industry and maintaining its global competitiveness in the twenty-first century. (Klinc & Turk, 2019)

• Industry 4.0 - networking. At the turn of the century, the term "Industry 4.0" initially appeared. Its core building blocks are cyber-physical systems or the networking of the physical environment. It is a mix of cyber and physical systems that describes the technologically structured industrial processes and the autonomous communication of equipment along the value chain (Smit et al., 2016). Industry 4.0 employs a virtual digital reproduction of the real world in terms of technology. It is built on the Internet of Things (IoT), Big Data, the Internet of Services, Smart Factories, and Advanced Manufacturing, all of which are components of today's digital environment. The fundamental distinction between Industry 3.0 automation and earlier versions was the presence of a human intermediate between the physical and digital worlds who input data on computers, reviewed computer printouts, and led events in the physical world. (FIEC, 2015) described Industry 4.0 as the digitization of the whole industry.

2.1.1 Cyber-physical Systems

In Industry 4.0, cyber physical systems are a key technical concept. A cyber-physical system is one that has a continuous automated link between the physical world and intelligent computer components capable of seeing, directing, and controlling it. Unlike traditional embedded systems, which are designed to be isolated devices, the focus of Industry 4.0 cyber-physical systems, according to Jazdi, is on networking multiple devices (2014). According to Santos et al. (2017), cyber-physical systems are an extension of embedded systems that bridge the physical and digital worlds by incorporating complex information processing from several networked physical elements (sensors, people, machinery, equipment, etc.).

According to Lee et al. (2015), a cyber-physical system has two key functional components: enhanced connectivity and smart data management, analysis, and computing capabilities. Based on this abstract guideline, a "5C (Connection, Conversion, Computation, Cognition, and Configuration)" architecture was established for practical reasons. (Muhuri et al., 2019)

2.1.2 Technological Building Blocks of Industry 4.0

There is no apparent consensus among scholars on the key technologies for Industry 4.0. (Vaidya et al., 2018). The figures differ depending on the researchers' perspective and understanding of Industry 4.0. The technological foundation for Industry 4.0, in our opinion (engineering), consists of six pillars:

1. Internet of People (IoP). A radically different Internet paradigm in which individuals are viewed as active participants rather than passive users of the Internet. (2017) (Conti et al.) This paradigm connects consumers, suppliers, designers, and manufacturers into a single whole by using historical Internet services.

2. Internet of Things (IoT). IoT technologies provide flawless interoperability and enhanced communication between the physical and digital worlds, with possible applications including smart homes, smart buildings, smart cities, and others (Faheem et al., 2018). The idea is to link everything that is sophisticated enough to be connected to the Internet and routed via it through a switch. Finally, everything that important will be outfitted with smart sensors that will monitor what is going on around them in real time. (Klinc & Turk, 2019)

3. Robotization and other forms of computer-aided manufacturing (CAM). It may translate digital data into material world layout (for instance, mounting, adding – digital printing, or deleting). The German I4.0 Working Group (2013) proposed the

phrase "smart factory" to characterize this new paradigm, which allows for significant improvements to previously established industrial processes.

4. Digital twin. The digital twin acts as a representation of the physical entity in the cyber-physical system, which is a vital component of Industry 4.0. (Uhlemann et al., 2017). A digital twin is a virtual replica of a physical adversary (Klinc & Turk, 2019).

5. Cognitive computing. This umbrella phrase includes big data, machine learning, cognitive algorithms, and artificial intelligence. This employs the previously described digital twin to attempt to simulate human cognitive processes in a computer model (Conti et al., 2017). proven that cognitive computing emulates how individuals examine and handle data in the real world (in the cyber world) (Klinc & Turk, 2019).

6. Computer cloud. Infrastructure for information and communication technology (ICT) offers storage, processing, and communication services as a utility, similar to how individuals pay for water, electricity, and heating. Virtualization of hardware and networks enables efficient access to required capabilities while also ensuring privacy, security, and resilience. Cloud-based solutions serve as platforms for improved integration of Industry 4.0 partners (Erboz, 2017), giving a variety of services to future smart factories to combine better production and logistics operations (Marques et al., 2017), and ultimately lead to cloud manufacturing (Marques et al., 2017) (Smit et al., 2016).

2.1.3 Construction 4.0

When incorporating highly creative concepts embracing cutting-edge technology into the conventional heavy industry, it is critical to note that, while being one of the most important industries, construction has one of the lowest R&D intensity levels. Similarly, worker productivity in the AEC has fallen over time, but it has almost grown in other industries (Oesterreich & Teuteberg, 2016). Oesterreich and Teuteberg (2016) identify and explain a number of structural difficulties in the industry that lead to the aforementioned poor numbers. (1) the intricacies of building projects, (2) the uncertainty of tangible and intangible constraints within each project, (3) a highly fragmented supply chain, (4) short-term thinking owing to the transient nature of construction projects, and (5) a rigid, change-resistant culture.

Nonetheless, the goal of Construction 4.0 is to maximize the benefits of huge digitalization of information and material processes, as well as large amounts of digital data about building items and the built environment provided by different sensors, cameras, builders, and users. Academic research agendas arise, as does the industrial context in which the AEC sector is co-shaping (Oesterreich & Teuteberg, 2016). (FIEC, 2017).

2.1.4 Digitalization of the construction industry

Although it is acknowledged that digital technologies are transforming and will eventually alter the built environment business (Salamak & Januszka, 2018), the construction industry has a reputation for being hesitant to adopt new technology (Klinc et al., 2009; Klinc, Turk & Dolenc, 2010). The digitalization of construction involves several sophisticated processes and technologies, including (FIEC, 2015b):

“• Industrial production (prefabrication, automation, 3D printing, etc.).

• Robotics (for performing repetitive and/or dangerous processes, use of drones for surveying, etc.).

• Digitally controlled building sites (equipment with sensors, inter-connected machines and processes leading to more fluid, faster construction with less errors, BIM, etc.).”

However, it should be highlighted that the AEC business is adopting Industry 4.0 in a different way than other industries. Construction 4.0 is closing in on the pattern for mass-production of consumer-specific items (one of Industry 4.0's goals) by searching for potential for industrialization and repetition of manufacturing, as well as keeping ever-unique products rather than mass and serial production. Building has always been concerned with the creation of one-of-a-kind, one-of-a-kind goods, and there have never been true examples of serial manufacturing inside the construction process. The AEC's manufacturing strategy may be regarded as large-scale craft production, with the end result often being a skyscraper, bridge, or dwelling. The primary goal of the industry is thus to industrialize the production of one-of-a-kind objects, as opposed to other industries, which aim to personalize the production of industrialized products. By digitizing them, dynamic and non-static value networks can become as successful as static value chains in traditional sectors (Klinc & Turk, 2019).

Despite the apparent benefits of adopting digitization in order to bring the construction industry up to speed, Oesterreich and Teuteberg (2016) identify a number of concerns that must be addressed when assessing digital readiness.

After declaring that cyber-physical systems are a critical component of Industry 4.0 and Building 4.0, it is vital to acknowledge that no other industry is more physically demanding than construction, which generates bigger volumes of products or products that span larger regions.

Construction 4.0 addresses the complete built environment, including its infrastructure. It is a massive effort for the building industry, with far-reaching ramifications for human existence, work, and leisure. As a result, Sector 4.0 represents a substantial challenge for the construction industry. The difficulty is worsened by the lack of an innovation culture in the construction sector, as well as the industry's demographics, which include a limited number of business leaders and a big number of small and medium firms with varied levels of technological maturity (Klinc & Turk, 2019).

2.2 Robotics in Architecture

Robots, or automatically reprogrammable, controlled machines, are commonly used to host a wide range of physical production activities, including "material processing (mechanical grinding, laser cutting), disassembling and assembling, drawing, welding, and handling inspection, bending, casting, and packaging operations" (Oxford Economics, 2019). The same robots may be fixed, mobile, or installed, and the latest versions are substantially AI-powered, making them even more sensitive and aware to their surroundings. According to the International Federation of Robotics, by the end of 2016, these robots accounted for around 86 percent of the global operating stock. The same industry has led in robots applications (Oxford Economics, 2019). Manufacturing, however, is evolving. There are AI collaborative categories in the modern day, including such cloud-enabled robots, that have come out to completely eliminate the gap between automated production and manual assembly (Hashim, 2014) (M. Rapanyane & F. Sethole, 2020). 'These cobots' will offer a lot of value to automated and/or mixed manufacturing, which demands a lot of handling, creativity, and vision (Oxford Economics, 2019). AI and robotics are both seen as critical components and branches of the forthcoming Fourth Industrial Revolution. As a result, significant scientific advances in biotechnology, quantum computing, AI, autonomous vehicles, and robotics are set to revolutionize the relationship between machines and humans, with robots at the forefront. Robots are rapidly being employed in logistics and storage, as well as other sectors of manufacturing (M. Rapanyane & F. Sethole, 2020).

For decades, manufacturing industries have celebrated the advancement of automation, and the automobile industry is a good illustration of this trend, as the entire process, from the fabrication of single parts to final assembly, is frequently totally automated (Balaguer & Abderrahim, 2008). However, architecture is lagging behind, particularly on-site construction. In comparison to other industries, the construction business has distinct characteristics that make automating a process difficult. In contrast to vehicle manufacturing, where a well-established system produces a standard piece repeatedly, each construction site or project is unique, necessitating a great deal of modification for each project. Furthermore, because there is no established or pre-existing reference that solves a similar set of issues, robotic automation in the construction industry is falling behind due to differences in building regulations, worker technical abilities, site conditions, and rigorous schedule and budget plans (Xu et al., 2019).

2.2.1 Three Reasons Why Robots Are Rising So Fast

1: Robots are becoming cheaper than human labor. Because of the falling real costs of the elderly population and other expensive machines, robots have been given priority. As with alternative exponential growth and advanced technologies in the power processing of extended battery lives, microchips, and smarter network benefits, the per-unit value of a wide range of technological components has increased dramatically, while the total unit price of robots has fallen by 11% from 2011 to 2016. In practice, growing labor costs in major manufacturing economies will have a significant impact on pricing dynamics. A suitable example would be China, where labor expenses in the industrial sector have risen steadily since 2008, reaching 65 percent in 2019. (Global Payroll Association, 2019) This is the norm not only in China, but also in South Korea, the United States (US), Japan, Germany, South Africa, and other nations, especially as the populations of these latter countries age. (2019, Oxford Economics) Having said that, it is also important to highlight that the aging population is being influenced, and this is occurring with the advent of robots, which do not age and are more effective since they are machines that can be taught to execute a certain task without payment. (Eureka, 2018) (M. B. Rapanyane & F. R. Sethole, 2020)

2: Robots are rapidly improving their skills. As robot technologies advance, they are employed in a wider range of contexts, in more sophisticated operations, and are installed more quickly. These robots have become more sensitive and collaborative to their surroundings due to modern technological advancements. This is all since for artificial intelligence, which has made learning and making judgments easier when they interact with other robots of their sort (Schwab, 2015). This practice also contributes to the deployment of robots in industries other than manufacturing (Oxford Economics, 2019).

3: Demand for manufactured goods is rising, and China is investing in robotics to establish itself as the world's largest manufacturer. Furthermore, increased demand for produced goods is increasing demand for robot inventory. China is usually regarded as a crucial role in this transition. This is due to China's growth as the world's largest car manufacturing site, as well as a significant manufacturer of consumer electrical batteries, gadgets, and semi-conductors, all of which are robot-intensive industrial businesses. 2019 (Investopedia) Despite this trend, China continues to make significant investments in its automation journey, with at least 68 robots per 10,000 people in general manufacturing, compared to 303 in Japan and 631 in South Korea. (Oxford Economics, 2019) (M. Rapanyane & F. Sethole, 2020)

Architectural construction is considered as one of the oldest crafts of the human being. As soon as ancient people settled down from nomadic life, they started building shelters for themselves. Since then, many advancements have taken place in terms of design strategies and materials for buildings, but the construction process still relies on human labor and techniques mostly. Despite huge advancements in technology, construction sites are considerably far from automation strategies. (Liu, 2009) One way of changing the old rules to gain more efficiency and safety in construction is deploying robotic systems in the process.

Robots, generally, have been designed to aid humans in complex, dangerous, and difficult tasks. The effectiveness of employing robots in different workflows has been proved in many industries. However, the architecture and construction industry have started putting these systems into their main process later than other industries. (Altobelli et al., 1993)

According to the findings of previous studies, construction managers consider that robot deployment is one of the most important aspects in increasing productivity (Bröchner & Olofsson, 2012) (Todhunter et al., 2019). To accomplish this, construction companies will need IT and computational programming experts on staff. A robot is made up of two parts: software and hardware, each of which requires a unique set of talents (Boulos et al., 2020). In the last couple of years, the interest in applying robotic systems in construction and architectural projects has increased. The main reason for this increasing interest is to enhance productivity and build up more effective control on fabrication and construction projects. In this context, robotic systems are used to mimic, and, finally, replace the existing manual construction processes. (Bonwetsch, 2015)

Furthermore, architects and designers are trying to investigate how different robotic systems and their variations can affect and change the primary stages of the architectural design. (Gandia et al., 2018) Hence, it can be declared that today, architects are not only using robotics for final construction purposes but also for design exploration. (Bonwetsch, 2015)

Below are some examples of implementation of robots in construction industry.

- Bricklaying robots: A bricklaying robot, often known as SAM (semi-Automated Mason), is one of the most recent potential innovations in construction. This bricklaying robot employs mechanical arms to pick up bricks, cover them with mortar, and precisely lay each brick. The workers' only responsibility is to fill the machine with bricks and clear up any excess mortar. The bricklaying robot (SAM) can lay 300-400 bricks per hour, easily 5 times faster than workers who can only lay 60-75 bricks per hour, indicating increased productivity and lower project costs. It can also free up workers' time so they can focus on more difficult jobs that humans are better at. (Boulos et al., 2020)

- 3D printing robots: 3D printing, which is utilized in design and architecture, is another technology that is having a significant impact. The 3D printer is controlled by a movable robotic arm that follows instructions. The first 3D printed bridge was produced in the Netherlands, and other 3D robots can construct a structurally sound building. With the advancement of new robotic technology, more and more buildings will be constructed using an automated construction method, increasing project productivity while lowering costs. (Boulos et al., 2020)
- Welding arms: Robotic welding is another example of the most advanced technologies that has been developed. To weld rapidly and precisely, robotic welding employs mechanized arms, welding positioners, and robot controls. Only a few workers are required to supervise robotic welding. There will be fewer injuries and no need to use manpower for manual chores if robotic welding is adopted. Project teams may focus on more critical tasks such as meeting deadlines, controlling budgets, and assuring productivity with the support of robotic welding equipment that performs the operation on its own. (Boulos et al., 2020)

2.2.2 Industrial Robots

Although the term robot covers a wide spectrum of mechanical machines used for automation, in this research, this term refers to 6-axis articulated arm robots, which are famously known as industrial robots or robotic arms. These robots, having three articulations to position in the space and three more for positioning their hand, are spectacularly established to handle material and different fabrication tasks. (Bonwetsch, 2015)

Robotic arms, in terms of being programmable machines, can correlate with Computer Numerically Controlled (CNC) tools such as laser-cutters, mills, and routers which have been adopted in fabrication processes during last decades. The combination of these machines with digital design tools has filled the gap between designing and having physical executions by allowing the designers to have a seamless flow of information with their fabrication tools. Additionally, this flow lets the designers have increased control over different steps of creating architectural artifacts compared to traditional methods. (Bonwetsch, 2015)

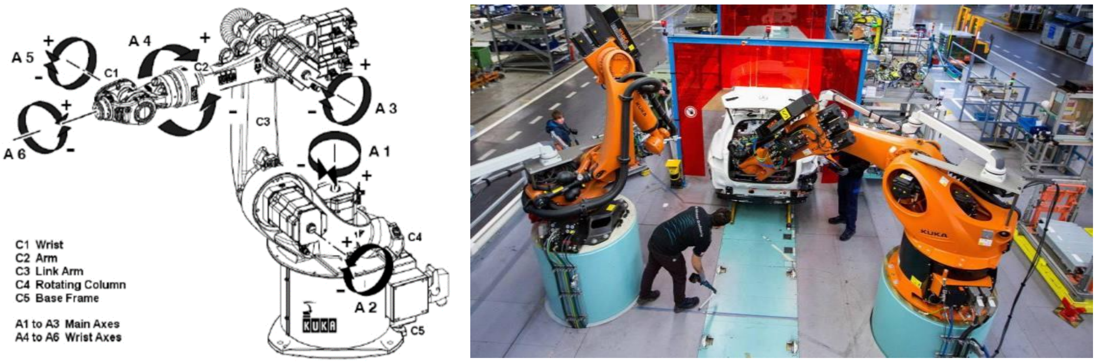

Figure 1: The kinematics of an industrial robot (left), and the use of robotic arms in the automotive industry (right).

However, industrial robots are not intelligent machines by themselves and their function is dependent on their control programmers. (Gandia et al., 2018) This fact results in opening a new space for research and exploration of how architects and designers can manipulate and combine robotic arms with other emerging technologies in order to design more intelligent and efficient processes of using these machines in AEC industry.

2.3 Robotic Brickwork

According to Altobelli et al. (1993), bricklayers are using the same methods used by the ancient builders in the City of Ur in ancient Iraq 6000 years ago. Brickwork is probably the oldest building method and material invented by human and it is remarkably adaptive and suitable for many architectural styles and purposes. (Bonwetsch, 2015) Even it is subject to many new research areas in architecture and design field.

 

Figure 2: Conventional Bricklaying (left), and a labyrinth constructed by robotic bricklaying (right). (Piškorec et al., 2018)

Automation in brickwork by means of robots has been subject to research since 1990s. (Altobelli et al., 1993) There are multiple reasons that make brickworks a suitable process to investigate the potentials of robotic fabrication in architecture. Firstly, brickwork can be isolated from the whole construction process and looked as an independent single project for automation. (Xu et al., 2019) Additionally, bricks, as small building units, have standardized shapes and their size and weight are perfectly suitable to be handled by industrial robots. More importantly, bricks and their geometry make it possible to develop large-scale purposeful geometries with a considerably high degree of freedom. (Bonwetsch, 2015) In other words, complex and large forms can be abstracted and constructed with a large number of bricks and their interrelations. Thus, controlling these members and their relations in a large quantity is one of the areas where digitally controlled design and fabrication gains advantages compared to traditional and human-based solutions. (Bonwetsch, 2015) In addition, brickwork is a good candidate for automation using robots because it is tedious, physically demanding, time-consuming, and causes irreversible back injuries for construction labor over time. (Liu, 2009)

For brickwork automation, Bonwetsch (2015) distinguishes between top-down and bottom-up representations. Bottom-up representation concentrates on the arrangement of the units and their local interactions while ignoring greater limits, whereas top-down representation divides a big, well-defined structure (wall borders) into smaller units (bricks). Top-down techniques are highly technical, stifling creativity and, as a result, neglecting boundary constraints, limiting bottom-up applicability to real-world situations. 2015 (Bonwetsch) A better representation would include both techniques, addressing a range of forms while being constrained by a boundary. Image-to-image machine learning translation models are viable alternatives to more declarative techniques. Machine learning models may generalize the content of the filler for any boundary condition based on picture representations (Isola et al., 2017). Simultaneously, machine vision technologies increase the robot's flexibility by enhancing its capacity to deal with variations in a present job. (Zandavali & Jimenez Garcia, 2019)

Figure 3: A robotically constructed brick wall. (Gandia, 2018)

Despite the fact that brickworks automation has been accessible for over 30 years, researchers have only just begun to investigate the programmability potential of the technology, turning away from engineering-oriented techniques and toward a design-oriented approach. The most significant disadvantages of brickwork automation were their inability to adapt to the site environment and handle deviations in the prescribed task. Previous research added mobility elements and feedback systems to industrial robots to improve the robot's response to site conditions. Developing a container to move the robot on site (Bärtschi et al., 2010), modifying tracks in the robot (Arch Union, 2018), and using an aerial structure to 'suspend' the robots are all options for mobility (Gramazio & Kohler, 2016) (Dörfler et al., 2016; Helm et al., 2014). (2016) combined mobility and data capture by outfitting industrial robots with a mobile track system and 2D and 3D scanners that detected objects or impediments. Collaborative robots with mobility systems are also another option for increasing robot site adaption (Willmann et al., 2012). (2014) published an Aerial Robotic Construction workflow that was tested using blocks assembling. One of the difficulties was ensuring the accuracy and consistency of placing a brick in the 'proper spot.' The 'flying' conditions' inconstancy was reflected in system precision. These efforts centered on combining hardware devices to expand the robot's site adaption capabilities, with small efforts to boost its flexibility in the bricklaying activity (Zandavali & Jimenez Garcia, 2019).

Two independent studies focused on task flexibility with clever algorithm solutions for two distinct reasons. These robots collect data from their surroundings and calibrate their precision based on the task at hand. Nair et al. (2017) trained a robot to manage a rope using a self-supervised machine learning model and imitation (Nair et al., 2017). EVA (Automata, 2018) is a tiny, unexpansive robot meant to learn by imitation. The human performs the movement and placement first, and the robot follows suit while calibrating the system to the surroundings. This study posits that rather than simply perceiving the world, the embodiment of automation might focus on building a system that understands it. It implies that the process of capturing the area to be filled, defining the borders, and calculating each brick location is intuitive and can be automated with the help of artificial intelligence (Zandavali & Jimenez Garcia, 2019).

2.4 Artificial Intelligence in Architecture

AI is a subfield of computer science concerned with the creation of intelligent machines that behave like humans. AI intelligent computer functions include learning, problem solving, speech recognition, and prediction (Habeeb, 2017). (M. B. Rapanyane & F. R. Sethole, 2020). As part of computer science's objective of generating machine intelligence, AI has become an essential feature of the technology industry. The vast majority of AI-related research is highly sophisticated and technical. Among the basic core AI goals are fundamental knowledge, vision, and the capacity to handle and move objects, with knowledge generation as an engineering significant part of AI research (Castrounis, 2019). However, it is equally important to demonstrate that the primary goal is to construct robots that can respond and behave like humans and are packed with tremendous amounts of information about the environment. (Habeeb, 2017)

Artificial Intelligence (AI) is widely being used in many industries such as healthcare, finance and banking, and even in agriculture. It has also been embedded in our daily life while we are using Google Search, Voice Assistants, and our smartphones. In all these cases, AI deploys computer processing for performing actions such as reasoning and decision-making that human brain does in a faster and more accurate way. (Russel & Norvig, 2002)

AI is also a good complementary for automation in AEC. Using construction robots for performing routine tasks such as bricklaying can noticeably be beneficial to accomplish the construction goals faster and, moreover, improve the precision, quality, and safety. However, every architectural and construction project has its own unique conditions and environments and this can bring about difficulties for employing robots in different projects. (Mohammadpoura et al. 2019)

In recent years, Architecture, Engineering, and Construction (AEC) Industry is looking forward to increasing automation in many fields to enhance not only productivity but also safety. Nevertheless, it is crucial to note that AEC is falling behind other industries in terms of implementing AI and other emerging technologies into its working processes. (Oesterreich & Teuteberg, 2016)

Since the Architecture, Engineering, and Construction (AEC) industry is one of the most important production sectors, it has a significant impact on economic balances, societal stability, and global climate change concerns. Its status quo, slow innovation rate, and conservative methods are also acknowledged in terms of its adoption of technology, applications, and procedures. However, in a highly competitive global technology landscape and sociopolitical landscape, a new technological era - Industry 4.0 fueled by AI - is driving productive sectors. (Maureira et al., 2021)

Artificial Intelligence can come up with numerous alternative options with a considerably more pace than architects and designers by helping them to overcome human limitations in handling large amounts of data. This, consequently, enhances the design process, planning, construction and operating in the Architecture, Engineering, and Construction Industry (AEC) which has been remarkably under-digitized compared to other Industries. In equipping AI in AEC, however, selecting a suitable technique for successful decision-making based on the knowledge acquired from the environment can be one of the important challenges. These techniques in AEC can be classified into two main areas: 1) Decision-making algorithms, and 2) Learning algorithms and methods. (Mohammadpoura et al. 2019)

2.4.1 Machine Learning Algorithms

Machine Learning is the study of mathematical and statistical models, algorithms, models, and application of Artificial Intelligence techniques that machines use for improving their performance by learning and improving from their experiences. Computers, with the help of machine learning techniques, can analyze data and learn from them similar to the way the human brain thinks and interprets information. (Mohammadpoura et al. 2019) In other words, machine learning is the technique of passing data, acquiring information about it, and making predictions or determinations about anything in the world via algorithms. Instead of using a set of instructions and hand-coding software routines, the machine is taught to use enormous volumes of data and programs that give it the ability to learn how to perform the task. (Habeeb, 2017)

Machine Learning (ML) has the ability to simplify and adapt the traditionally time-consuming and expensive setup of digital integrated design to manufacturing workflows, opening new possibilities for architectural production. The capacity to swiftly construct and change these processes is crucial in the context of Industry 4.0, especially in order to generate mass customized goods, referred to as lot size in the Industry 4.0 paradigm (Ramsgaard Thomsen et al., 2020).

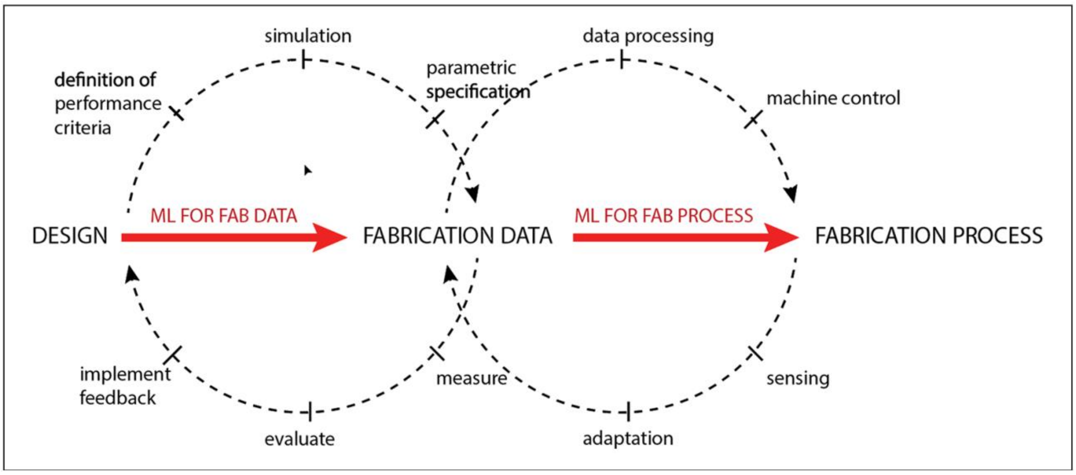

Figure 4. Positioning the two discrete moments for machine learning in fabrication within the Digital Chain's existing stages. The graphic depicts a cyclical relationship between design and fabrication, with forward channels showing how design influences fabrication and backward channels showing how design and fabrication data must be adjusted in response to feedback. (Ramsgaard Thomsen et al., 2020)

Hence, combining Artificial Intelligence techniques with construction robots can fill in this gap and result in more intelligent robotic techniques with the power of learning and decision-making in different circumstances.

2.4.2 Unsupervised Learning and Clustering

Unsupervised Learning is a type of machine learning employed in the processes in which there are only input data but no output data. The aim of using unsupervised learning is to find regulations and patterns among the input data independent from the output. (Darko, 2020) One method of unsupervised learning is Clustering, which is used to find groupings or cluster the input data based on their similar features. (Alpaydin, 2016) With this method, we can easily separate the clusters, label them as classes and try to classify them according to their special properties and features.

In this study, clustering is going to be used for detecting and classifying the different types of bricks and then use these clustered bricks wherever they are needed in the bricklaying process.

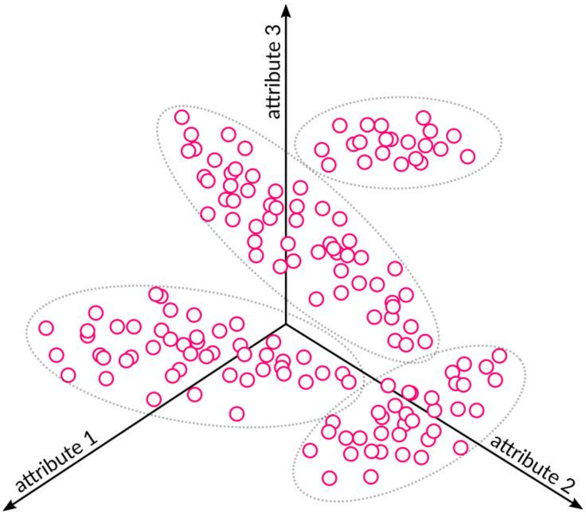

Figure 5: A diagram of the Gaussian Mixture where attributes are defined to determine groupings. (Nate, 2018)

2.4.3 Deep Learning and Neural Networks

In the last half-century there has been a significant success in achieving high-accuracy learning algorithms with the help of big data and powerful computers. This advancement has caused less manual interference and brought about an autonomous approach that learns and is not fixed only for specific tasks. These algorithms, called deep neural networks, start from the raw input, combine the values of preceding levels in each hidden layer and learns more complicated aspects and functions of the input and provide outputs that are learned by the most abstracts concepts in the final layer. (Alpaydin, 2016) According to Yeh (2006), neural networks are strong algorithms for optimization which work with developing systems that demonstrate self-organization and adaptation in a similarly simplified manner to the biological systems. The main idea in deep learning is to learn feature levels of increasing abstraction with minimum human interaction. This is due to the fact that in most cases the structure of the input is so complicated that becomes almost a hidden concept and it is essential to extract these patterns and regulations during training from a large sample of examples using developed algorithms. (Alpaydin, 2016)

2.4.4 Reinforcement Learning

Reinforcement learning, according to Alpaydin (2016), is a method of learning with critics. In this method there is a decision-maker called an Agent which is placed in an environment. A reinforcement learning program, basically, generates an internal value for the different actions and states of the agent inside the environment to define how they affect the process to lead to the final goal. Once such an internal reward mechanism is learned, the agent develops to take actions that maximize the reward and achieves the final solution to the task. In contrast with other learning methods, there are no external resources that provide the training data in reinforcement learning. Here, the agent itself performs actions in the environment and generates data by gaining feedback as a reward. This feedback updates the agents' brain and teaches it to take actions that return higher rewards.

Reinforcement learning algorithms have wider opportunity of application and have the potential to create better learning machines even though these algorithms are slower than supervised learning algorithms. The advantages of this method such as learning with no supervision needed end-to-end training, from raw input to actions, encourages the researchers to scale its applications into more complex scenarios. (Alpaydin, 2016)

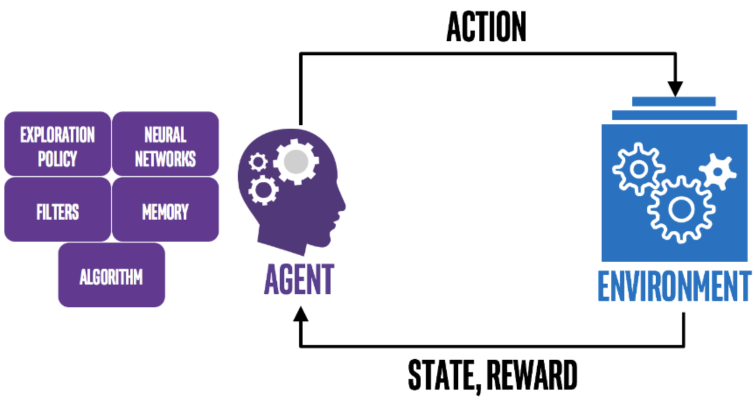

Figure 6: An overview of how Reinforcement Learning works. (Lee, 2020)

2.4.5 Q-learning and Its Paradigms

One of the most often used representative reinforcement learning algorithms is Q-learning, which is an off-policy technique. Since its inception, several studies have detailed Q-learning applications in reinforcement learning and artificial intelligence difficulties. However, there is a knowledge gap on how to apply and combine these complex algorithms in a larger artificial intelligence process. Primitive Q-learning algorithms were inefficient in a variety of ways and could only be used to solve a small number of issues. This highly strong algorithm has also been observed to learn inappropriately and overestimate the action values on occasion, decreasing overall performance. However, as a consequence of recent advances in machine learning, new variants of Q-learning, such as Deep Q-learning, which integrates basic Q learning with deep neural networks, have been developed and widely used (Jang et al., 2019).

Reinforcement learning (Chapman & Kaelbling, 1991) has received considerable attention recently, and it has had a great success in fields including game theory, operations research, information theory, simulation-based optimization, control theory, and statistics. Reinforcement learning, a type of machine learning, is quickly gaining popularity in computational intelligence as a method for allowing computers to make their own judgments in a given environment without prior knowledge or labeled data (Jordan & Mitchell, 2015). With new varieties of reinforcement learning being launched and the possibilities of future reinforcement learning usage rising substantially, artificial intelligence will continue to push cross-cutting improvements (Parisotto et al., 2019).

Reinforcement learning is a powerful learning algorithm that learns the optimum policy without having to model it by interacting with the environment (Kober et al., 2013). It utilizes an agent that learns the value function for a specific policy through interaction with the environment in order to foresee an ideal solution, and it evolves and learns the best policy based on the value function on a continuous basis (Tesauro, 1995). Temporal-Difference (TD) learning (Boyan, 2002) is the most widely used approach in reinforcement learning applications. It combines the Monte Carlo (Gilks et al., 1995) method of evaluating value without the need of a model with the advantages of dynamic programming (Puterman, 2014), which can approximate the value using only current estimates. Q-learning uses an off-policy control that divides the deferral and learning policies and uses Bellman optimal equations and the e-greed policy to update action selection (Watkins & Dayan, 1992).

Q-learning has been the basis for many new reinforcement learning algorithms because it has easy Q-functions comparing to other reinforcement learning algorithms (Dearden et al., 1998). However, early Q-learning systems were limited by the incentive storage problem (Lazaric, 2012). As the number of actions rises, the available storage space becomes insufficient, preventing the problem from being solved. In other words, obtaining effective learning for complicated learning problems with large state-action contexts is difficult. Furthermore, in compared to single-agent environments, the state storage space for multi-agent environments expands, and this storage occupies a significant percentage, if not all, of the computer memory (Lazaric, 2012). As a result, the machine is unable to deliver the proper response. To handle this challenge in varied situations, many Q-learning algorithms have been created.

Temporal-Difference (TD) learning (Boyan, 2002) combines the Monte Carlo (Gilks et al., 1995) method of assessing value without a model with the advantages of dynamic programming (Puterman, 2014), which may estimate value using just current estimations. Q-learning uses an off-policy control to segregate the deferral and learning policies and to update action selection using Bellman optimal equations and the e-greed policy (Watkins & Dayan, 1992). (Zhang & Yang, 2017) (Gu et al., 2017) (Ghavamzadeh et al., 2015).

Deep Q-learning (Hester et al., 2018), developed by Google in 2016, is a well-known technique for single-agent situations. In this paper, we look at techniques for coping with Q-learning issues in multi-agent systems. Modular Q-learning (Tham & Prager, 1994) is a multi-agent Q-learning system that separates a single learning issue into many portions and applies a Q-learning algorithm to each. Ant Q-learning (Dorigo & Gambardella, 1996) is a technique in which agents share reward values with one another, in the same way as ants reject lower reward values and solve problems with higher reward values. In a multi-agent system, this makes it easier to acquire the action's reward values. The Nash Q-learning algorithm (Yang et al., 2020) is a multi-agent adaptation of the standard Q-learning algorithm.

Q-learning was primarely used in the fields of process control (Jiang et al., 2017), chemical process, industrial process automatic control, and airplane control (Khan et al., 2012). Q-learning is now employed in network management (Alsheikh et al., 2014), mostly for route optimization and reception processing in network communication. With the introduction of AlphaGo, substantial study in the field of game theory is underway (Vamvoudakis et al., 2017). The properties of reinforcement learning via trial and error are quite identical to those of the human learning process (Moerland et al., 2018). As a result, Q-learning is excelling in the field of robotics, particularly in the fields of autonomous vehicles, drones, and humanoid robots (Plappert et al., 2018). Figure 7 depicts the evolution of reinforcement learning.

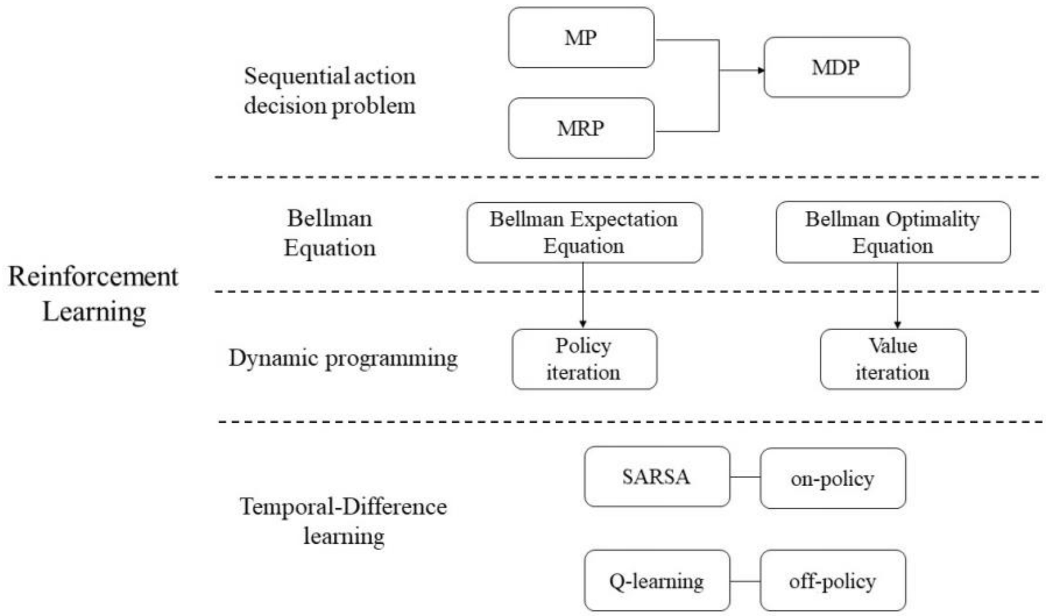

Figure 7: The flow of reinforcement learning

"The Markov decision process (MDP) (White III & White, 1989) defines the sequential behavior decision problem that is the foundation of reinforcement learning. The MDP specifies an agent that introduces the concept of the value function for learning, and the value function is associated to the Bellman equation. To develop the Bellman equation, reinforcement learning use MDP and the value function, followed by Q-learning to solve the problem. It is critical to select an efficient method that solves the Bellman equation" (Sutton, 1995) to enhance the efficiency of reinforcement learning. MDP, the value function, and the Bellman equation are all discussed in this section.

2.4.5.1 Markov Decision Process

The sequential action choice problem is mathematically defined as MDP. The environment is probabilistic, which implies that the state of the transition and the compensation are random after the action. Policies are rules for selecting actions to be performed in a certain state, and MDP can be used to formulate reinforcement learning algorithms. (Even-Dar & Mansour, 2001)

1) State

The state is a group of S observable agent states. "Observation of your situation" (Cassandra, 1998) is what state means.

2) Action

In a state S, an action is a collection (Sutton et al., 1999) of possible actions A. In most cases, an agent's set of actions are similar in every state. As a result, one A set is represented. (Littman, 2001)

3) State Transition Probiblity Matrix

When an agent performs action A, the state transition probability is a numerical representation of the agent's migration from state S to state S'. The following states and MDP compensation are decided completely by the current state and actions. As a result, the likelihood and size of the next state being compensated by the following compensation are given by. “The probability is:

$$Pass' = P[St+1 = s'|St = s, At = a]$$

where Pass’ is the probability recorded in the matrix P of moving to state s’ when action a is performed in state s, and t denotes the time.” (Littman, 2001)

4) Reward

The reward is the information that is delivered to the agent in the environment so that the agent can learn it. “When the state is s and the action is an at time t, the agent obtains the following reward:

$$Rass' = E[Rt+1|St = s, At = a]$$

where Rass’ is the definition of the reward function. t is the time, and E is the expected value for the reward to be given as action a occurs when it moves from a state to s’.” (Littman, 2001) The agent can describe the compensation value as an anticipated value since it can offer various rewards even if the same activity is performed in the same state depending on the environment. When the agent takes action A in state S, the environment informs the agent about the next state S' the agent will reach and the reward it will get. The agent receives information from the environment at time t + 1. As a result, Rt+1 represents the pay that the agent will receive.

5) DISCOUNT FACTOR

The notion of a discount factor was established in response to complications caused by compensatory procedures. After operating in each state, the agent gets rewarded. The value of a reward decreases with time, giving rise to the idea of depreciation. Depreciation has a value between 0 and 1, and it decreases the agent's income over time (Sutton et al., 1999).

6) Policy

When an agent reaches a given state, it selects an action based on the policy.

$$\pi(a|s) = P[At = a|St = s]$$

where π is the probability of policy that the agent selects a in state at time t. Reinforcement learning progressively learns better policies than the present one to attain an optimum policy. (Dietterich, 2000)

2.4.5.2 Value Function

The agent must chose the action it will perform in order to determine the future reward. The criterion that decides which policy is optimal is the value function. The value function is the total of the projected benefits when the policy is implemented from its present state (Dietterich, 2000) as follows:

“$v\pi\ (s) = E\pi\ [Rt{+}l + \gamma\ v\pi\ (St{+}1)|St = s)$

where the expectation equation Vπ (s) is the expected value Eπ, Rt+1 is the reward value to be awarded next and l is the discount factor. (Littman, 2001)” The state value function computes the total of the rewards that will be gained when the state is supplied using the formula above, allowing the agent to pick a more advantageous state.

The action value function checks at the state as well as the action. The agent chooses an action based on the Q-function. The Q-function is defined further down:

$$q\pi\ (s, a) = E\pi\ [Rt+1 + \gamma\ q\pi\ (St+1, At+1|St = s, At+1 = a)$$

The following equation expresses the relationship between the Q-function and the value function:

$$v\pi\ (s) = \Sigma a\in A\ \pi(a|s)q\pi\ (s, a)$$

For all actions, the policy and the Q-function value are merged together. The Q-function and value function are expressed using Bellman equations. The Bellman equation displays the link between the value function of the present state and the value function of the future state.

2.4.6 Bellman Equation

1) Bellman Expectation Equation

The value function represents the expected value of a state. The value function of a state is the total of the rewards to be collected when the agent moves to the next state, and it is impacted by the present agent's policy. The Bellman equation, which reflects policy, explains the link between the value function of the present state and the value function of the next state. (Dietterich, 2000), (Irodova & Sloan, 2005).

$$V\pi'(s) = \Sigma a\in A\ \pi(a|s)(Rt+1 + \gamma\ \Sigma s'\in S\ Pass'v\pi(s'))$$

Above is the Bellman expectation equation. $\Sigma a\in A\ \pi(a|s)$ is the probability policy to do the action $\Sigma s'\in S$ Pass' is the state transition probability matrix. As in previous equations, $Rt+1$ is the reward, and γ is the discount factor.

2) Bellman Optimality Equation

The purpose of reinforcement learning in the MDP scenario is to obtain the optimal policy. The policy is determined by the value function, and the optimum policy is the one which delivers the highest expectation for all policies. The Bellman optimum equation is a policy that uses the value function to find the best value. The Bellman optimum equation is as follows:

$$v*(s) = maxa\ E\pi[Rt+1 + \gamma\ v*(St+1)|St = s]$$

where maxa $E\pi$ is the maximum expected value among the policies that agents can receive. To address the MDP issue, reinforcement learning employs the Bellman expectation equation and the Bellman optimum equations.

2.5 Basic Q-Learning

Unlike previous algorithms that did not differentiate between behavior and learning, Q-learning used an off-policy method to separate the acting and learning rules. As a result, even if the action taken in the next state was mediocre, the information will not be incorporated in the updating of the present state's Q-function, creating a quandary (Dietterich, 2000). Q-learning, on the other hand, solves the problem by utilizing an off-policy method. The Q-value equation is as follows:

"$Q(s, a) \leftarrow Q(s, a) + \alpha[R + \gamma \max Q(s', a') - Q(s, a)]$

where α is the learning rate and has a value between 0 and 1. R is a reward and γ is the reduction rate of the reward as time passes." (Dietterich, 2000)

The action's Q-value for the current state S is Q. (S, A). To update S, the sum of the existing value Q (S, A) and the equation calculating the best action in the current state is employed. To continue Q-learning, the Q-value for each state is continuously updated using the above equation. Before beginning Q-learning, the Q-table contains rewards. If an agent uses a policy to pick an action in the first state, it then advances to the next state using a state transition probability matrix. When the

Q-table is used to solve a problem, this procedure is repeated until the total Q-value converges to a certain value (Irodova & Sloan, 2005). Q-learning is a Bellman problem solution that combines dynamic programming and Monte Carlo methods. Q-learning has been the core of various reinforcement learning algorithms because, unlike other approaches, it is simple and exhibits good learning capacity in single-agent circumstances. However, with Q-learning, a value is only altered once per action. As a result, it is difficult to handle complicated problems efficiently in a large state-action context since the agent may be inexperienced with the multiple states-actions. In addition, because the Q-table for rewards is pre-programmed, a large quantity of storage memory is necessary (Shoufeng et al., 2008). In a multi-agent system with two or more agents, a large state-action memory is required, which poses issues. As a result, simple Q-learning algorithms have limited ability to perform effective learning in a multi-agent setting (Jang et al., 2019).

2.6 Robotic Control via Reinforcement Learning

In the context of Industry 4.0, one of the most critical challenges of Cyber-Physical Production is to have not only economically efficient but also adaptive and flexible production methods under different circumstances. Motion planning of the industrial robots is one of the areas that employing more flexible techniques is crucial due to their variability in motion tasks and their need to adaptively cope with the variations in the environment. (Oesterreich & Teuteberg, 2016) Commonly, the movements of these robotic arms are programmed in a non-adaptive way that a small change in the environment or circumstances will lead to error and failure in the whole process. For example, programming a pick-and-place movement requires the exact coordinates of the object to pick and the detailed location of the point to locate the object. (Meyes et al. 2017) In this method, a slight deviation in these coordinates or the path between can cause a total failure.

To solve this type of problem and achieve adaptability in robotic fabrication, one approach is to adopt artificial intelligence techniques such as Reinforcement

Learning algorithms. Previous researches have proven that RL agents and simulations are capable of learning how to perform specific actions and movements with industrial robots without any prior programming and path planning. (Andrychowicz, 2017)

Additionally, extending these robots with visual sensors or cameras has been tested to successfully generalize the learned actions for further various actions with no need for more learning processes. The idea is to provide the robots with the capability of observing their environment using sensor technologies and cameras and gather experiences while taking actions. Using these observations, robots can adapt their movements according to the changes in their environment. (Meyes et al. 2017)

In general, augmenting the industrial robots with Reinforcement Learning algorithms and training them with RL-based simulations, provides the ability to adaptively deal with the variations in performing particularly similar tasks without the need to program them from scratch over the time. This fact results in saving large amounts of time and costs in fabrication projects and, moreover, is a fundamental step to allow robots to accumulate expertise over their lifetime similar to human labor. (Meyes et al. 2017)

CHAPTER 3

PROBLEM DEFINITION

3.1 Problem Definition

As discussed previously, the architecture and construction sector has not fully developed dominant strategies to exploit the potentials of new technologies such as artificial intelligence and robotic systems which have been used effectively by other industries since couple of decades ago. These technologies can be put into action in many phases of architectural process from basic design stages to final on-site construction and increase the efficiency of projects in terms of time, economy, and accuracy. Moreover, implementing intelligent unsupervised robotic techniques in the construction phase of architectural projects could be a fundamental and game-changing solution for on-site risks and threats for human labor in terms of work safety.

The Fourth Industrial Revolution is taking place and changing many industries and manufacturing methods. In the context of Industry 4.0, one of the most critical challenges of Cyber-Physical Production is to have not only economically efficient but also adaptive and flexible production methods under different circumstances. However, by a simple investigation in AEC Industry and especially the construction sites, it will be obvious that the existing techniques and methods are remarkably far from the standards of Industry 4.0, the era that we are living in.

Hence, the problem with applying old methodologies in architectural construction processes can be abstracted in four main parts:

- The construction process is inefficient and inadequate compared to the standards of Industry 4.0 which emphasize automation, smart manufacturing, flexibility, and adaptive processes.

- Manual fabrication techniques include several types of risks for human labor on construction sites.
- It also, limits the creative design process due to insufficiencies in existing fabrication methods and lack of flow between concept design, prototyping, and fabrication.
- Furthermore, the mentioned technologies use of which can be noticeably advantageous for developing automation in AEC, generally, have technical difficulties to be directly occupied by architects and construction professionals. These difficulties include demand for high programming skills for deploying AI methods and being familiar with robotic control.

Hence, these problems should be solved by introducing more intelligent processes where human interaction and manipulation are minimized and replaced with smarter automation processes and methods of human-robot collaboration on construction sites.

3.2 The Objectives of This Research

By investigating the potentials of new technologies in hand, this research is going to introduce an intelligent process for architectural robotic fabrication using artificial intelligence techniques and algorithms. The primary goal is to minimize the manual decision-making and manipulation of robot movements by architects or construction specialists. The provided method has the capacity to assist architects and designers to easily adopt automation in their workflow without the need to focus on complex technical concepts and techniques of AI and robotic systems, which can be tedious and demanding for them in many terms. With approaching this level of automation in robotic construction, manual and outdated human labor construction process could be replaced with a convenient flow of collaboration between laborers and smart agents of construction, providing safety, precision, and speed.

Due to the reasons discussed previously, this research focuses on a case study of intelligent robotic bricklaying using a simulation-based research design and can be extended to other tasks that need smart automation with robots in the process of design and fabrication.

Mainly, this research aims to explore the potentials of using reinforcement learning algorithms and environments for robotic fabrication in architecture and building industry. To explore these potentials, objectives of the research are as followed:

- Simulate an environment consisting of:
    - A primitive form designed to be built by bricklaying,
    - And an intelligent decision-making agent which will perform the process of bricklaying; in this case, the intelligent agent is a simulation of an industrial robotic arm in the environment.
- Training the intelligent agent for unsupervised bricklaying using reinforcement learning algorithms and dynamic programming.

3.3 Hypothesis

The hypothesis of this research states that by integration of latest AI advancements to the existing robotic construction methods, we can train robots as intelligent agents to perform human labor tasks on construction sites.

CHAPTER 4

METHODOLOGY AND RESEARCH DESIGN

4.1 Research Design and Methodology

As discussed, this research is going to investigate the potentials of implementing artificial intelligence techniques into existing robotic bricklaying methods in order to establish a smart process of employing robots by architects, designers and construction specialists. For this purpose, different artificial intelligence algorithms and techniques have been explored and tested to find the suitable options that meet the requirements and objectives of the research. Exploring the potentials of Evolutionary Algorithms, Genetic Algorithms and Metaheuristic methods, it was discovered that in addition to these existent methods, Reinforcement Learning algorithms could also feasibly satisfy the objectives of this research. The advantageous features which make these types of algorithms to pave the way for a novel area of research and fit our demands can be listed as below:

- Certain Reinforcement learning algorithms are simulation-based and can be properly integrated with architectural and fabrication simulations providing real-time visual and physical feedback and analyses.
- These algorithms consist of an environment and an agent or multiple agents trying to learn to perform a wide range of tasks which they are assigned for.
- Various types of RL environments are suitable for solving complex problems not only in discrete but also in continuous action spaces. This can provide a range of dynamic tools in hand for training agents to accomplish multiple types of tasks.
- More importantly, these algorithms are considerably more enhanced and evolved compared to other groups of AI algorithms that can provide a human level precision, intelligence, and control in learning and performing assigned

tasks in architectural projects that formerly only human labor were capable of.

4.1.1 Research Tools

To approach the objectives of this research, a set of tools and materials are required. As the aim of the research is to prove the hypothesis based on a set of simulations, the tools and materials are computer software, object-oriented programing languages, a series of artificial intelligence algorithms, and a personal computer to run the simulations on.

The software adopted for this set of simulations are Rhinoceros which is a Computer Aided Drawing tool and Grasshopper plug-in, a visual programming interface to carry on the primitive design and connect the algorithms on a platform which will provide practical control features specially for designers and architects. Other plug-ins such as KUKA PRC are employed to simulate and visualize robotic arm application on required objectives.

In addition to the mentioned tools, Python, an object-oriented programing language and related libraries such as NumPy are used to construct the core algorithm and environments for training and controlling the agents. These algorithms include codes for generating the environment, RL algorithms which are the main training algorithms and other supplementary dynamically programmed codes to complete the process.

4.2 Research Design

4.2.1 Simulation Process

To explore and test the application of suggested methods, a simulation process is designed to interconnect the capabilities of Rhino and Grasshopper software as conventional CAD and visual programming tools for architects and designers with the outstanding potentials of RL algorithms. Therefore, the different stages of this simulation are designed in different environments which are connected and synchronized dynamically.

The simulation design for this research is divided into four main stages:

a. Primitive form design:

First, the geometry and other characteristics of the prototype that is going to be the subject to construction in the simulation are designed. This prototype can vary from a simple flat wall to more complicated forms and patterns which have the brick as their building units. The form is developed via conventional CAD or parametric design environments such as Rhinoceros and Grasshopper. This step is the starting but raw phase of the project which makes the foundations for the next stages.

b. Block and stacking layout generation:

After having the basic design in hand, the next step will be to generate a layout of blocks of the wall and another layout of bricks as a pile; at the next stages, the first layout will be used as the target of placing the bricks and the second one as the target of picking the bricks in the process of bricklaying simulation.

For generating the brick layout for robotic assembly, the initial prototype mesh will be divided into smaller segments of the size of the blocks that will be used as construction units. At this step, the center points of each of the segments are the center points of the blocks. These center points, at the next step of the simulation, which is training the robotic arm the pick and place process, will be used as the target points for the agent to try to place the bricks on.

The second generated layout of blocks is the layout of a pile consisting of the required number of bricks in a certain array. The center points of each block in this array are the target of robotic arm to reach and pick bricks.

The dimensions of the layouts in 'number of bricks' are defined after initiation. These dimensions are the width and height of the prototype wall, and length, width, and height of the pile of bricks which will be used in the next steps for the training and tracking the observations of the agent. This step of the simulation is also performed by supplementary plug-ins of Grasshopper in Rhino platform.

c. Pick and Place Training for the Arm:

The most important stage of the simulation is where the robotic arm will be trained for bricklaying via reinforcement learning algorithms. Reinforcement learning is a method of training an agent in an environment with a system of reward and critics. In this method, the intelligent agent starts to explore the environment within several episodes and steps. In any of the steps, the agent gets a positive or negative reward based on its performance compared to its goal and at the end of each episode, the accumulation of these rewards will give the agent a statistical insight of its performance to evolve for the next steps and episodes. Thus, by deploying these algorithms, the simulated robotic arm needs to take actions and cumulate positive or negative critics based on the system of rewards which is programmed based on the goal of the simulation. By collecting these rewards, the agent learns to take the actions which are in favor of the main goals of the process and avoid unnecessary and sometimes adverse actions.

There are successful examples of employing RL algorithms for industrial robot motion planning for different purposes such as pick-and-place, laser cutting, or even playing the wire-loop game. (Andrychowicz et al., 2017).

However, in this case, these algorithms are going to be used to train the robotic arm two main objectives:

i. Selecting a series of blocks from the pile layout for picking

ii. And, selecting a series of targets from the prototype wall layout for placing the block in.

In other words, during this stage, the agent in the environment will explore various actions to learn a policy for solving the bricklaying problem by picking correct blocks and placing them at the correct targets. For this, the agent extracts an optimal list of blocks from each layout to perform the pick and place of bricklaying process.

iii. Approach:

To accomplish the mentioned objectives, an approach which is a combination of dynamic programming and Q-learning algorithm is designed and employed to train the agent. Below is the description of how this approach functions.

1. Generating a random array of n block IDs to pick:

With the layout of the pile of bricks generated at previous steps, each brick is assigned with a unique ID according to its position in the pile layout. At this step, the algorithm generates a random array of these block IDs with the size of n, which is the number of total bricks required for building the prototype. This array goes through operations and produces the optimal array of suitable bricks for picking from the pile after the training phase.

2. Generating a random array of n block IDs to place:

Simultaneously, another random array of block IDs is generated that demonstrates the list of targets on which the bricks will be placed. The IDs of each block is similarly defined by the position of each block in the stacked layout of the prototype. The size of this array is n in like manner.

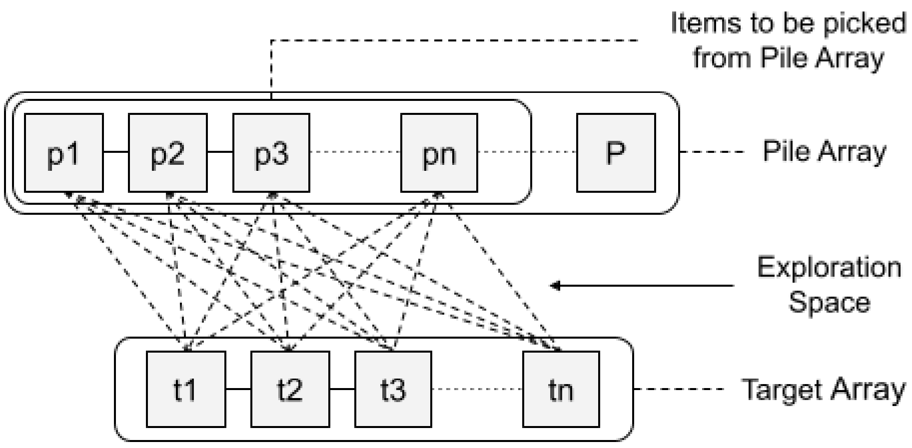

Figure 8: Generating arrays and exploring the space for learning

Pile Array = [n:p Block IDs], Target Array = [n Bock IDs]

Where n is the number of blocks needed to construct the prototype and p the number of blocks in pile layout (p > n).

a. Go through each array and check for the availability of the block IDs at each step:

At this stage, the algorithm examines the array of the pile and the array of the targets to check for the availability of each item in each array. For this problem, available items are the block IDs the corelated bricks of which are positioned in the first layers of the layouts at each iteration. After this examination, the first layers of each layout are updated if any available items are selected from the layout.

b. Assign a rewards system for the available and unavailable items in each array:

While inspecting the items of each array, the RL agent receives positive or negative rewards if the array item is respectively available or unavailable. These rewards are the q-value of each action taken by the agent at any step and as the training continues, the agent takes actions that have more q-values; in other words, the agent choses the actions that maximize the accumulated reward and avoid the actions that minimize this amount.

3. Training the agent to modify the arrays based on the system of rewards:

After defining the system of rewards, as the agent starts to take actions, it receives positive and negative rewards based on the state of the environment. These actions, states, and the rewards are collected as observations of the agent in a table named Q-table. Learning the policy and predicting the future actions and their q-value are extracted from the data stored in the Q-table. In this method, the formula to calculate and predict the q-values for each future action is:

$$Q(s, a) \leftarrow Q(s, a) + \alpha[R + \gamma \max Q(s', a') - Q(s, a)]$$

where α is the learning rate and has a value between 0 and 1. R is a reward and γ is the reduction rate of the reward as time passes.

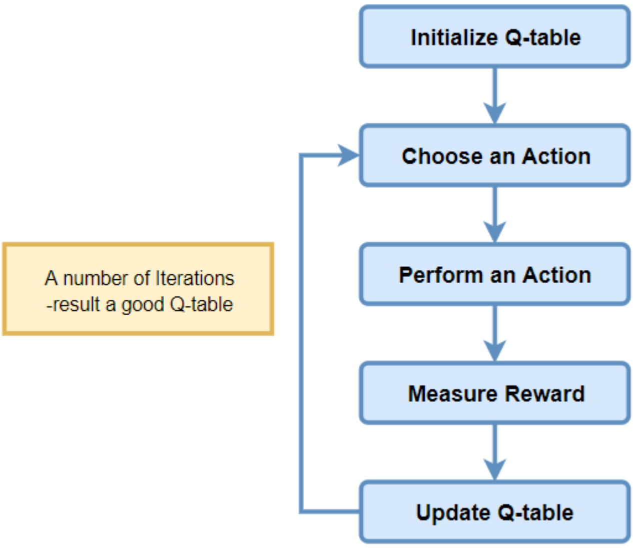

Figure 9: A demonstration of how Q-learning functions

a. Commencing from the random arrays:

To begin to explore the action space, the agent takes the initially generated pile and target arrays, check availability of their items and collect observations.

b. Continue with more random modifications:

After the first iteration at which the initial arrays are examined, the agent starts to modify the arrays randomly at next steps. At the early steps, the agent will perform more random actions of modification in order to explore wider range of solutions and hence collect more complete sets of observation. Therefore, he episodes at which more random actions are performed are called exploration episodes.

c. Decreasing the randomness of the modification based on the observations and learnt policy:

Once the agent passes the exploration episodes of learning and accumulates sufficient sets of observations, the q-table will provide more precise insights for future actions, states, and q-values. With more observations in hand, the agent continues to decrease the randomness of the actions and increase their precision around the optimal solutions. These episodes at which the actions are more precise rather than random and in favor of accomplishing higher q-values, are called exploitation episodes.

d. Iterating until the policy is trained to the agent:

By increase of the number of episodes in the training phase, while the agent has explored and exploited the environment and the action space, the q-table provides a certain pattern of actions for the agent to accomplish its goals. This pattern is called a policy and once it is learnt by the agent, its decisions will evolve in terms of precision.

4. Finding the optimal solutions:

After an adequate number of episodes of training and when the policy is learnt by the agent, the optimal solutions for the problem emerge. Thereafter, the algorithm collects these solutions for the next stages of the simulation. In the scope of this research, the optimal solution is extracting two arrays of items:

a. The pile array: a list that contains n numbers of the IDs of the blocks to be picked from the pile layout by the robotic arm in an optimal order.
b. The target array: a list containing n numbers of the IDs of the blocks to be placed on target in the prototype layout by the robotic arm in an optimal order.
c. Exporting the optimal solutions for pick and place:

   At this stage, the pile array and the target array which are the final outputs of the algorithm for the problem are exported to Grasshopper environment to function as the inputs of pick and place process by the robot.

d. Robotic bricklaying simulation:

   The last step of the simulation is to perform a complete bricklaying application of the robotic arm. At this step, the KUKA PRC plug-in for Grasshopper is employed to simulate the operation. The plug-in receives the exported arrays as inputs to transfer a set of point-to-point movement commands to the robot. Additionally, the type of the industrial robot, the type of its virtual tool and other parameters can be selected and manipulated using the plug-in. In the case of this simulation a virtual KUKA KR30/60 robot and a Schunk PGN160 gripper are assembled to perform the assigned tasks.

Figure 9 demonstrates a summary of research design and tools corelated with each phase of process:

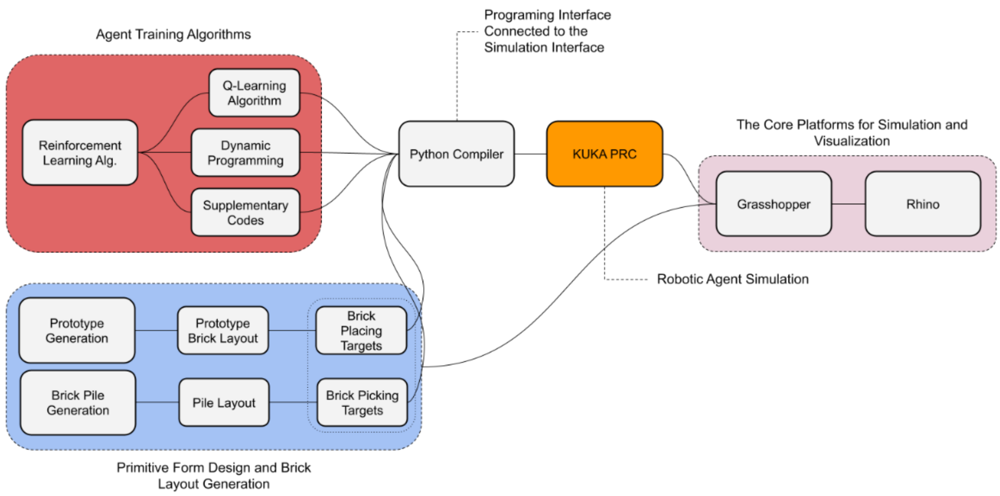

Figure 10: A visual summary of research design and materials

4.3 Studying Variations to Test the Proposed Simulation

To test the functionality of the proposed method and algorithm, five different scenarios are generated with variations in pattern of layers in four different prototypes. In this study, the variations of the prototype is generated within the parametric design platform and the functionality of the algorithm to train the agent to solve the problem of bricklaying is put into challenge. During each variation, separate training sessions have been conducted and the results are put to comparison in the next chapter.

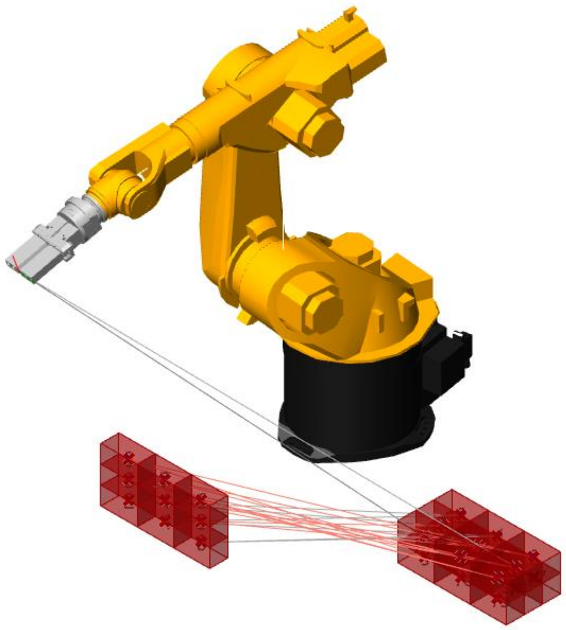

Figure 11: Robotic setup for pick and place simulation.

4.3.1 Prototype Variations

Each initial prototype is individually designed to challenge the different capacities of the proposed method in this research. The prototypes vary in number of blocks, number of layers, stacking pattern, and environmental constraints. In addition, during the training process, the learning parameters have been manipulated to explore a wider range of solutions for the bricklaying problem.

4.3.1.1 Prototype 1

This prototype is a flat two layered stack of blocks. The total required number of blocks to fabricate this prototype is 10. The first prototype is designed to test the basic ability of training the arm to fabricate a small-scale layered structure.

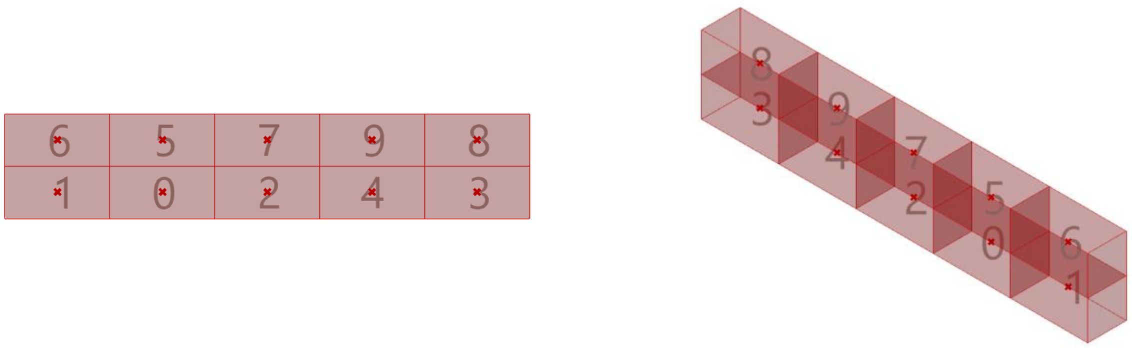

Figure 12. Prototype 1

4.3.1.2 Prototype 2

The second prototype consists of total nine blocks which are stacked in three layers of three blocks. In terms of form and pattern, this prototype is a flat wall likewise.

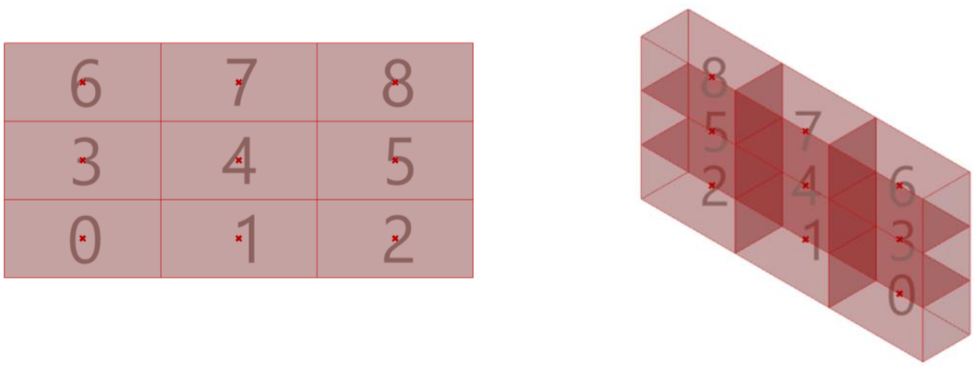

Figure 13. Prototype 2

The reason to design this prototype for the learning process is to explore the capabilities of the method in different dimensions for the layers: more layers but fewer blocks in each layer compared to the first scenario.

4.3.1.3 Prototype 3

The prototype number three also contains nine blocks in total three layers. However, in this case, the stacking pattern of the layout is different from the previous cases. The pattern includes free distances between the blocks of each layer.

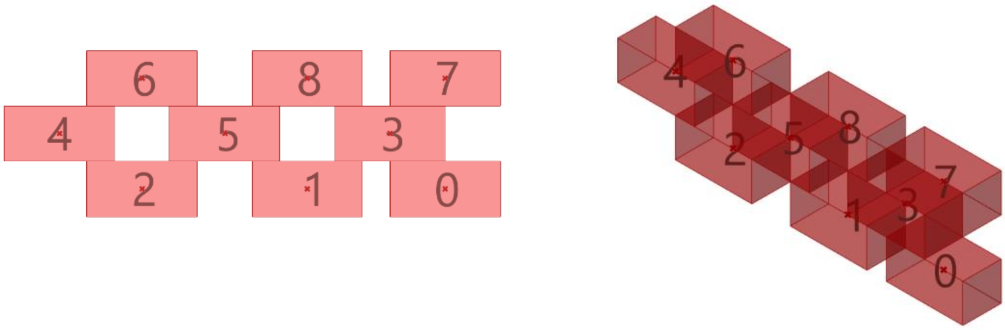

Figure 14. Prototype 3

Testing the method using this prototype explores the potential of the proposed method for performin automated bricklaying of special patterns in small scales.

4.3.1.4 Prototype 4

The final prototype alike the prototype 2 and 3 includes nine blocks in three layers. Nevertheless, in this case the stack is put under a different environmental circumstance which is an uneven base which affects the pattern of the target layout.

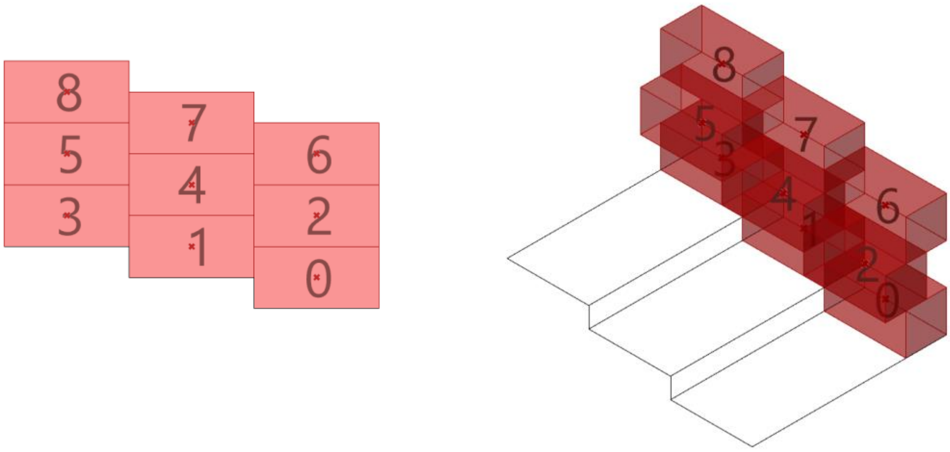

Figure 15. Prototype 4

4.3.1.5 A Prototype with Higher Numbers of Blocks

This prototype is generated to test the capacity of the algorithm in solving problems with larger dimensions. Hence, a wall with block number of 30 and layer size of six is designed as the prototype. At this simulation the pile layout is updated to provide enough blocks for picking.

4.3.1.6 The Pile Layout

In the simulations to test the algorithm on different four prototypes, the layout of the pile which nests the blocks to be picked is constant and does not change. Hence, the pile is a layout of 18 blocks contained in two layers of nine. However, the pile is updated in the case of fifth prototype to meet the requirements of the problem.

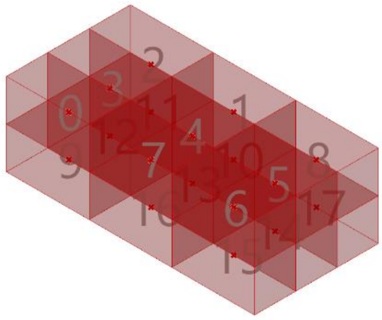

Figure 16: Pile Layout

Results and Conclusion

5.1 Results and Analysis

As discussed in the previous chapter, to assess the performance of the methodology that has been designed for training a robotic arm to solve a bricklaying pick and place problem using Q-learning, a subcategory of reinforcement learning, five different cases have been studied. These cases are arranged in different circumstances under which the size, pattern, and other characteristics of the prototype change. Therefore, the algorithm is put to different challenges by these alterations.

After conducting the simulation and training process for the planned scenarios, it has been observed that the algorithm has promising potentials to solve the assigned problem in a greedy manner for certain number of blocks. Nevertheless, by increasing the number of blocks of the problem to higher numbers, as the exploration space enlarges drastically, the pace of the algorithm to approach the optimal solution declines by a noticeable amount.

The observations accumulated from the different scenarios indicate that, employing Q-learning as a method of reinforcement learning has outstanding potentials to solve smaller scale bricklaying problems where precision is a key requirement of the process. In addition, it has been observed that, solving this problem with the proposed method can train robots to handle a wide range of variations not only in the fabrication prototype but also in the conditions of the environment where the bricklaying is being operated. This, accordingly, exposes the advantageous potential of the designed method to be employed in real construction site situations, where unanticipated and random working environments are common.

5.1.1 Analysis of Scenario 1

In this scenario, the generated prototype is a linear small-scale wall with 10 total block numbers. The wall has two layers in which lay five blocks. On the other hand, the generated block pile consists of 18 blocks with dimensions of three, three, and two as width, length, and height respectively.

As it is evident in Figure 17, the algorithm has successfully trained the agent to solve the problem in approximately 100 total episodes. In this training, each episode consists of 50 steps. Thus, it can be calculated that the agent has learnt the policy after 5,000 numbers of actions.

The fluctuations in the reward amount around episode number 20, genuinely, depicts the tendency of the agent for more exploration of the action space whenever the state does not reach noticeable progress by repeating actions.

Analyzing the results of the first scenario proves that the proposed method is capable of solving the bricklaying problem of a 10-block wall by reaching the optimum reward of 20 which represents 10 successful picking actions and 10 successful placing actions.

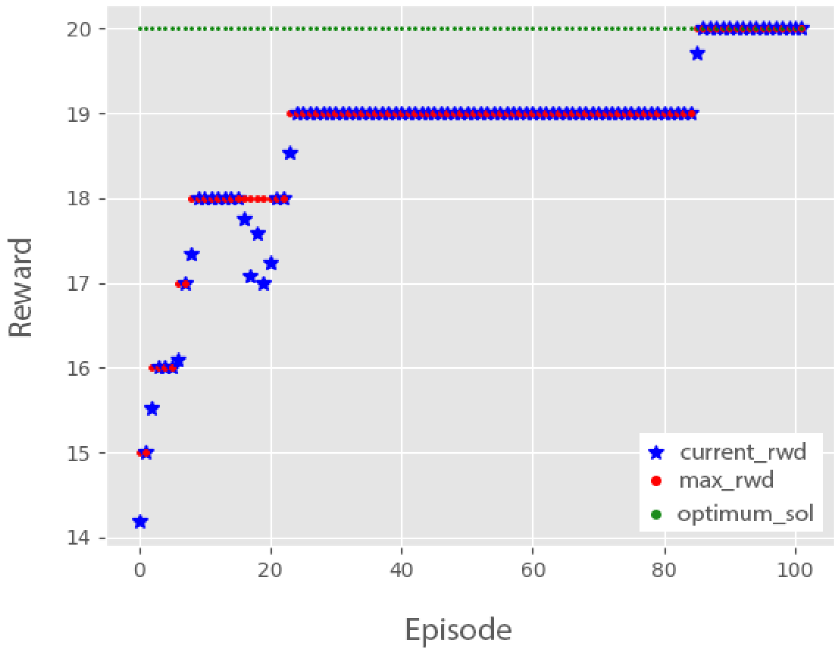

Figure 17: Reward per episode for Scenario 1

5.1.2 Analysis of Scenario 2

The generated prototype in this scenario is another small-scale wall with ten9 total block numbers. There are three layers to the wall, each with three blocks. The created block pile, on the other hand, is made up of 18 blocks with width, length, and height measurements of three, three, and two, respectively.

Figure 18 visualizes the results of the training for this scenario in terms of rewards per episodes. As it is clear in the figure, the training has been successful in approximately 40 episodes of 50 steps. This implies that the agent has approached the optimum solution within 2,000 actions.

In comparison with scenario 1 where there exists 1 more block in each layout, it can be comprehended that the algorithm has solved the problem of the current scenario in considerably smaller number of actions.

The overall ascending fluctuations of the episode rewards in this figure indicates that increasing the number of layers of the prototype results in a larger exploration space in the problem and reduces the initial learning rate of the agent compared to the first scenario.

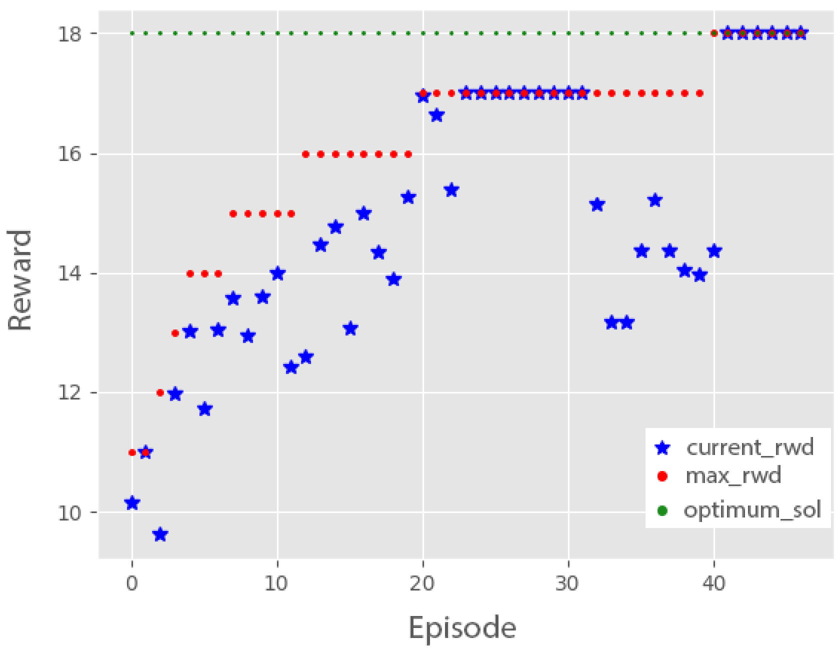

Figure 18: Reward per episode for Scenario 2

5.1.3 Analysis of Scenario 3

Within this scenario, the number of the blocks and the dimensions of the prototype are the same as the second scenario; nine total blocks divided into three layers. Likewise, the pile layout is unaltered. Nonetheless, the distinctness of this scenario is the block pattern of the prototype where the blocks of each layer have a half-block distance from each other.

Analysis of Figure 19 demonstrates that in this scenario the optimum solution has been discovered within approximately 40 episodes, as same as in the previous scenario. This similarity in the learning rate of these two consequent scenarios uncovers the fact that the pattern of the block layout is not a decisive factor in the process of learning as the agent handles the IDs of the blocks in layers independent from the pattern of stack.

The above-mentioned characteristic of this algorithm makes it an advantageous method to perform robotic bricklaying of complex patterns generated with bricks.

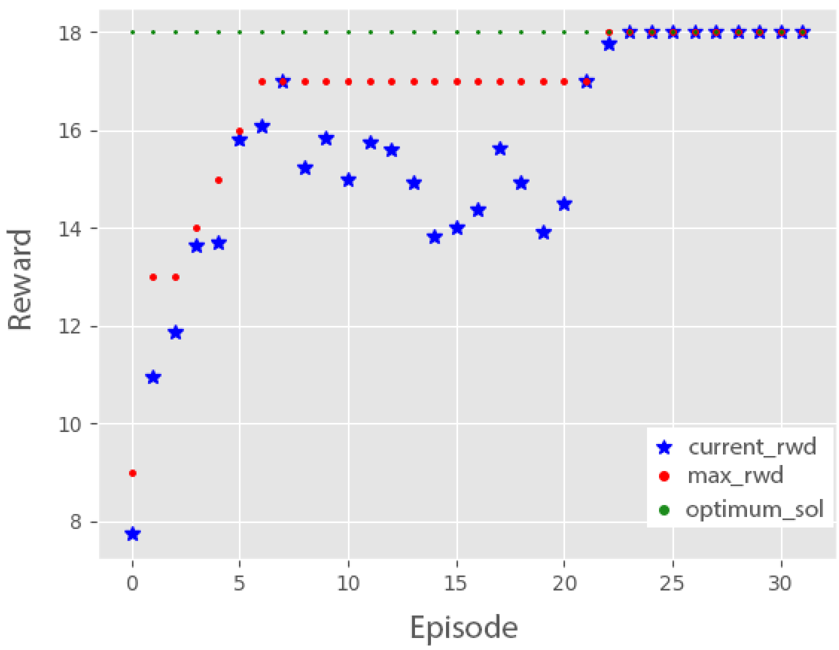

Figure 19: Reward per episode for Scenario 3

5.1.4 Analysis of Scenario 4

The number of blocks and prototype dimensions in this scenario are the same as in two previous ones; nine total blocks separated into three layers. The pile layout is also unchanged. However, in this scenario the variable factor is the surface of the base of bricklaying.

Applying automated robotic bricklaying on most of the construction sites faces crucial problems when the circumstances of the environment are non-standard. Hence, this scenario is dedicated to solving the bricklaying problem under circumstances that might be observed in real situations; bricklaying on an irregular surface.

The results visualized in figure 20 indicates that the learning rate has not been affected by the changes in the environment drastically and the optimum solution has been discovered by approximately equal number of steps and episodes compared to previous two scenarios.

The aim of assessment of the method in this scenario is to disclose its potentials for being implemented in non-standard conditions which is a constant issue in actual construction projects.

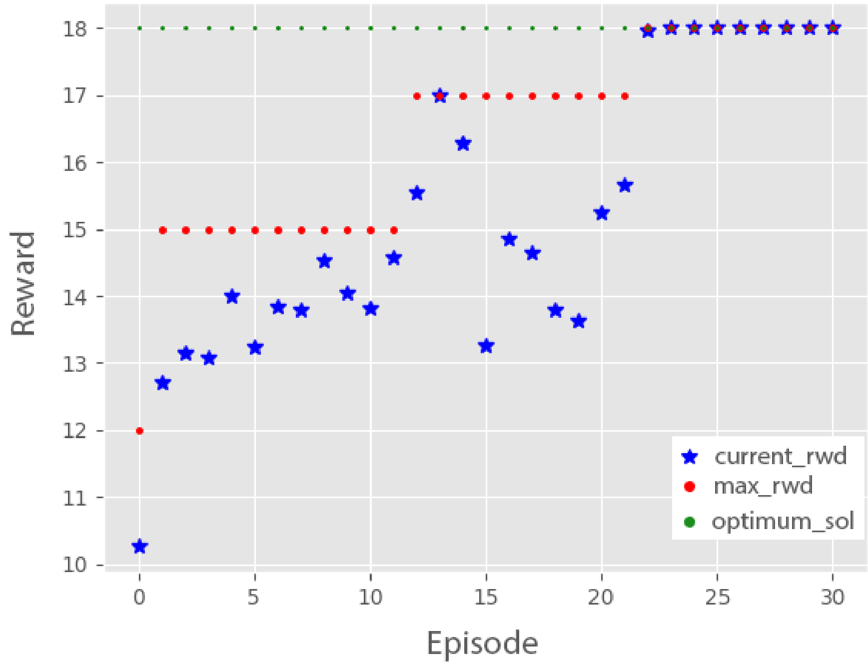

Figure 20: Reward per episode for Scenario 4

5.1.5 Analysis of Scenario 5

After investigating the potentials of implementing the method proposed within the scope of this paper on four different small-scale prototypes under various conditions, in the last scenario a large-scale prototype is generated for the simulation.

In this scenario, a larger flat wall with totally 30 blocks divided into five layers is used as the fabrication prototype of the simulation. Consequently, the pile layout dimension has been updated to four blocks in width, four blocks in length and three blocks in height, producing a sum of 48 blocks of which 30 will be picked to construct the prototype.

Conducting the training simulation with this setup, it was discovered that as the number of blocks and layers of the prototype increases, the exploration space exponentially multiplies in size. As a result, the learning rate of the agent declines to zero after a certain steps of trial. Figure 21 demonstrates that after more than 2,000 episodes of 50 steps (100,000 actions), the algorithm is not capable of solving the problem. Compared to small-scale prototypes, it can be concluded that the proposed method, which is training a robotic arm with Q-learning to perform automated bricklaying, is not applicable to large-scale prototypes.

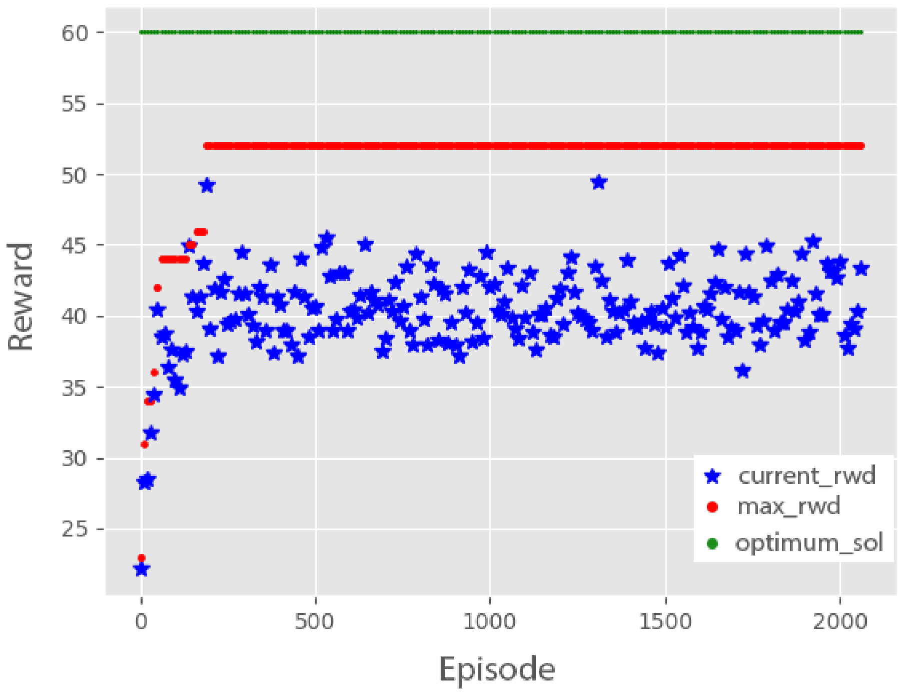

Figure 21: Reward per episode for Scenario 5

5.2 Conclusion

The Fourth Industrial Revolution is underway, transforming numerous businesses and manufacturing methods in order to meet the enormous worldwide demand for various products and services by utilizing every technological advancement accessible. Furthermore, one of the most essential problems of Cyber-Physical Manufacturing in the context of Industry 4.0 is to have not only economically efficient but also adaptable and flexible production techniques under various circumstances. However, a basic inspection of the architecture business, particularly construction sites, reveals that current procedures and practices are remarkably distant from the requirements of Industry 4.0, the period in which we now live. By paving the road for the integration of cutting-edge technology into diverse industry processes, we can bring about significant improvements to make architecture one of the industries capable of meeting emerging needs in the context of Industry 4.0.

Studies on incorporating elements of Industry 4.0 into architectural construction projects have shown that the integration improves the industry in a variety of ways which are discussed in the primary chapters of this research.

In light of this, and with the goal of incorporating certain contemporary technologies into an ancient building process, this study looks into the possibilities of integrating artificial intelligence (AI) approaches into existing robotic bricklaying processes to create a smart procedure for architects and designers to utilize robots. Although there have been studies and implementations of robotics in the architectural design and fabrication process over the last few decades, the developed methods can still be improved in many ways, allowing architects and construction specialists to benefit from more intelligent and productive tools in both the design and construction phases. Adopting new breakthroughs in artificial intelligence approaches that are being developed and employed in other industries is one of the numerous features that can be applied in construction employing robotics.

After investigating through different artificial intelligence methods, the most practical set of these algorithms, which is also one of the most advanced artificial intelligence algorithms, was selected as a tool to approach the research's objectives. Reinforcement Learning algorithms, which function based on a simulation of an environment and an intelligent agent being trained to perform certain objectives, are chosen for training our intelligent method of employing robots in architectural fabrication process.

To test and validate the hypothesis of this study, which is that by combining the latest AI developments with existing robotic building methods, we can train robots as intelligent agents to do human labor duties on construction sites, a multi-step research strategy was implemented. This simulation-based research follows a flow from developing basic prototypes to training a robotic arm to build the prototypes via bricklaying as the intelligent agent. To meet the research aims, several platforms and tools have bene merged in this research design, which have been discussed thoroughly in the related chapters. Finally, several simulations and training sessions have been conducted and the produced results have been put to analysis and comparison in the first part of this chapter.

In summary, the analysis of the results of the designed scenarios demonstrated that employing reinfocement learning algorithms for training industrial robots to perform human labor tasks brings about advantageous outcomes in construction scenarios where precision in repeatitive tasks is a fundemental requirement. In addition, with the assist of these enhanced algorithms, robotic arms can learn to perform these tasks under varying construction and environment situations without any need to reprogramming or other prereuirements. With the results observed, we can declare the proposed method in the scope of this research is proved to be functioning correctly according to the objectives defined in the third chapter.

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