Optimization of Knitting Path of Flat Knitting Machine Based on Reinforcement Learning

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***Abstract*—In the textile industry, the flat knitting machine plays a crucial role as a production tool, and the quality of its weaving path is closely related to the overall product quality and production efficiency. Seeking to improve and optimize the knitting path to improve product effectiveness and productivity has become an urgent concern for the textile industry. This article elegantly streamlines and enhances the intricate weaving process of fabrics, harnessing the formidable power of reinforcement learning to achieve unparalleled optimization of weaving paths on a flat knitting machine. By ingeniously integrating reinforcement learning technology into the fabric production realm, we aspire to elevate both the quality and production efficiency of textiles to new heights. The core of our approach lies in meticulously defining a state space, action space, and a tailored reward function, each meticulously crafted to mirror the intricacies of the knitting process. This model serves as the cornerstone upon which we construct an innovative knitting pathway optimization algorithm, deeply rooted in the principles of reinforcement learning. Our algorithm embodies a relentless pursuit of excellence, learning from its interactions with the dynamic environment, embracing a methodical trial-and-error approach, and continuously refining its decision-making strategy. Its ultimate goal: to maximize the long-term cumulative reward, ensuring that every stitch contributes to the overall optimization of the weaving process. In essence, we have forged a groundbreaking collaboration between the traditional art of fabric weaving and the cutting-edge science of reinforcement learning, ushering in a new era of intelligent and efficient textile production. Through this process of iterative optimization, the agent can gradually learn the optimal knitting path. To verify the effectiveness of the algorithm, we performed extensive experimental validation. The experimental results show that reinforcement learning can significantly improve knitting efficiency, improve the appearance and feel of fabrics. Compared with traditional methods, the method proposed in this article has a higher level of automation and better adaptability, achieving more efficient and intelligent knitting production, with a 10% increase in production efficiency.**

Keywords—Flat knitting machine; reinforcement learning; weaving path optimization; textile industry

I. INTRODUCTION

In today's booming textile industry, the flat knitting machine stands as the cornerstone equipment, its performance being a direct determinant of both production efficiency and product quality. Notably, the selection of the knitting path holds immense significance, as it critically shapes the final product's appearance, hand feel, and overall production efficiency [1, 2]. However, traditional knitting path optimization methods are heavily reliant on manual expertise and repetitive trials, making them inefficient and unable to keep pace with the escalating complexity of knitting requirements. Consequently, the textile industry faces a pressing need to explore novel optimization techniques that can enhance the performance of flat knitting machines.

In recent years, the swift advancements in artificial intelligence technology have offered an efficacious solution for enhancing the operational optimization of microgrids. Notably, the reinforcement learning algorithm stands out as a prominent tool, as it transcends the reliance on historical data and pre-defined labels. Instead, it actively engages with the environment through iterative learning, fostering a dynamic and adaptive approach. Traditionally, the optimization of power system operations entailed modeling the intricate system mechanisms and subsequently solving these models under stringent constraints. However, reinforcement learning disrupts this paradigm by eliminating the need for an explicit physical model of the system. It possesses the remarkable ability to discern and refine the operational model purely from the available data, thereby significantly accelerating the learning process and enhancing the efficiency of modeling the system's operations. This shift underscores the transformative potential of reinforcement learning in driving the future of microgrid optimization. At the same time, based on the "trial and error" behavior of reinforcement learning, continuous learning can be carried out through interaction with the environment, and the accuracy of the model and the optimization of parameters can be continuously improved. Therefore, compared with the traditional micro-grid control mode, reinforcement learning can organically connect the components of the system, interact and cooperate with each other, and complete complex optimization work with a small amount of prior information, improving the operation ability and efficiency of the micro-grid. At the same time, the practical application and improvement of the algorithm in different scenarios can also effectively improve the application effect of reinforcement learning.

The rapid advancements in artificial intelligence have ushered in reinforcement learning as a groundbreaking machine learning technology. Extensively applied to various optimization challenges, reinforcement learning leverages the interactive learning process between an agent and its environment to autonomously discover optimal decision strategies. This approach offers a promising solution for tackling intricate problems, making it a compelling candidate for revolutionizing knitting path optimization in the textile industry. In this context, this paper will discuss the knitting path optimization method of flat knitting machine based on reinforcement learning to improve the knitting efficiency and product quality.

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II. Multi-axial Warp Knitted Fabric Production Equipment and Technology

A. Fibrous Raw Materials

The range of raw materials for warp knitted multi-axial fabrics is very wide. The lining usually adopts high performance fibers with good mechanical properties, such as glass fiber (GF), carbon fiber (CF), Kevlar fiber, ultra-high molecular weight polyethylene fiber (UHMW. PE), etc. It can be a low twist flexible staple yarn or a non-robbing high performance filament yarn. When used as reinforcing yarns, high-performance untwisted filaments are generally used, and sometimes the yarns can be slightly twisted for ease of weaving. Yarns are generally thick, up to about 2500tex.

Polyester low elastic yarn, glass fiber yarn, etc. can be used for ground weave yarn. When polyester yarn is used for ground weave more than glass fiber, due to the high requirements for yarn fineness and bending stiffness, the technical parameters of wire drawing are improved, and thus the cost is greatly increased. Therefore, in actual production, raw materials should be selected according to the requirements of composite material properties and applications.

Glass Fiber (Glass Fiber) is a new type of engineering material, which is made of inorganic glass added with silica oxides such as calcium, boron, sodium, iron and aluminum. The molecular arrangement is a three-dimensional network structure, so the properties of glass fiber are homogeneous [3]. It has excellent properties such as non-combustible, corrosion-resistant, high-temperature resistance, low moisture absorption, and small elongation. It also has excellent characteristics in electrical, mechanical, chemical, and optical aspects, but the disadvantages are brittleness and poor wear resistance.

1) Production process of glass fiber: The production of glass fiber has a long history, and there are two main types at present: one is the method of replacing platinum to increase the pot to make glass into balls, and put the balls into the crucible furnace made of platinum pound alloy to make a leak plate, and the glass melt flows out of many leaks on the leak plate, and is wound on the high-speed rotating wire winding Jane; The second is the pool method: the glass powder is directly put into the pool cellar to melt, and the glass melt flows out through the leaky plates and nozzles installed on several sub-channels. The wire drawing method is the same as before. Glass fibers are generally 3-10 um in diameter, and more recently 13um, 15um, 24um monofilament yarns have been used. Due to the characteristics of glass fiber in structure, performance, processing technology, price, etc., it has always occupied an important position in the composite material manufacturing industry.

2) Types of glass fibers: Based on their distinct raw materials, glass fibers can be categorized into the following types:

C glass fiber, alternatively known as medium-alkali glass, possesses characteristics that lie between E glass fiber and A glass fiber. While it excels in chemical resistance, its electrical performance is inadequate. Furthermore, its mechanical strength falls short by 10% to 20% compared to alkali-free glass fiber.

In overseas markets, medium-alkali glass fiber is predominantly utilized for the production of corrosion-resistant glass fiber products. Conversely, in China, this type of glass fiber holds a prominent share, exceeding 60% of the total glass fiber output, and finds extensive applications. It is widely employed as reinforcement in Fiber Reinforced Polymers (FRP), as well as in the manufacture of filter fabrics and wrapping materials. This prevalence stems from its cost-effectiveness, offering a significant price advantage over alkali-free glass fiber, thereby fostering robust competitiveness in the domestic market.

High-strength glass fiber: It is characterized by high strength and high modulus. It is mostly used in military industry, space, bulletproof armor and sports equipment. However, due to the high price, it cannot be promoted in civilian use at present, and the world output is only about a few thousand tons.

E-CR glass. This is an enhanced boron-free and alkali-free glass that is utilized to craft glass fibers exhibiting exceptional acid and water resistance. Specifically, its water resistance surpasses alkali-free glass fiber by a remarkable seven to eight times, while its acid resistance significantly outperforms that of medium-alkali glass fiber. It is a new variety specially developed for underground pipelines, storage tanks, etc.

B. The Basic Properties of the Polymer Optical Fibers

The application of optical fiber to luminescent fabric must take into account the necessary properties of luminescent fabric and the performance characteristics of optical fiber. The necessary attributes of luminescent fabric include soft, light, durable and safe for use, high and uniform luminescent brightness, and good performance. The most prominent feature of the luminous fabric is the luminous brightness and flower pattern effect in the dark. The luminous brightness refers to the light flux per unit projected area. Factors such as fabric stretching, fabric type [4], fabric density, number of optical fibers, fiber bending radius, fiber bending loss [5].

The mechanical properties of optical fibers affect their weaving properties [6]. The collusion strength of optical fiber is low, poor elasticity and tolerance, so the optical fiber is easy to break in the process of weaving. Quartz fiber and glass fiber bending performance is poor, polymer fiber fracture tensile rate is larger, good toughness, good bending performance [7], bending radius, but the bending radius of polymer fiber and weaving process when the yarn bending radius is inconsistent, and polymer fiber bending rigidity, not conducive to fiber bending into circles. Therefore, it is difficult to weave polymer optical fiber into circles, and it is easier to weave through the form of floating line. Polymer fiber flexibility, flexure and elongation, good, easy to process and use [8].

Fig. 1 shows knitting path optimization process under the framework of reinforcement learning. The thermal performance of optical fiber affects the dyeing and shaping of optical fiber luminous fabric. Quartz fiber and glass fiber have good heat resistance, polymer fiber has poor heat resistance, low melting point, poor thermal stability [9], and it is easy to damage the fiber in the case of acute heat or cold, increasing the loss of polymer fiber. The working temperature of PS core and PMMA core polymer fiber is less than 80℃, and the working temperature of PC core polymer fiber is less than 150℃. The heat-resistant polymer fiber can be used in the range of 100℃-200℃ [10, 11], so it is difficult for the polymer fiber fabric to iron, dye, shape, etc.

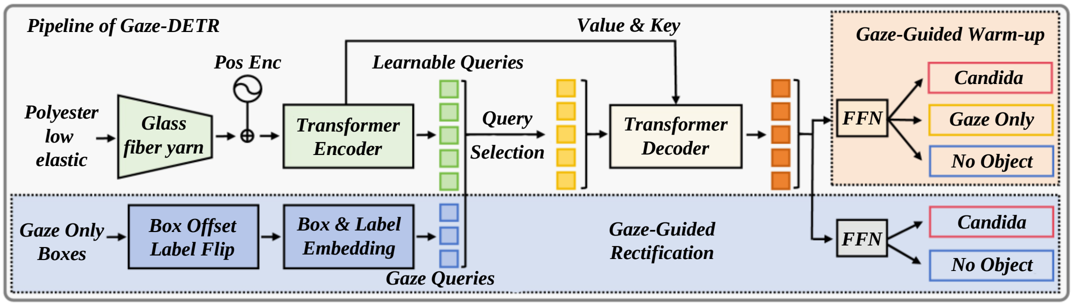

Fig. 1. Knitting path optimization process under the framework of reinforcement learning.

The chemical performance of optical fiber generally depends on its raw materials. For instance, the performance of glass fiber closely resembles that of glass, while the chemical properties of polymer fiber align with those of plastics. However, the unique structure of optical fiber itself can also significantly influence its chemical properties. Specifically, the large surface area of optical fiber facilitates the absorption of moisture and susceptibility to corrosion, thereby diminishing its compressive resistance and light transmittance. While polymer optical fiber exhibits robust acid and alkali resistance, strong corrosion resistance, and aging resistance, it is prone to corrosion by acetone, hexane, acetone mixed reagents, ethyl acetate, and other reagents.

Optical fibers exhibit distinct optical properties, encompassing both light conduction and scattering, which directly impact luminescence brightness, visual effects, and intricate floral pattern manifestations. Notably, polymer fibers are characterized by pronounced dispersion, a high refractive index, and substantial optical transmission attenuation, particularly pronounced in the ultraviolet and infrared spectra. However, within the visible light spectrum, polymer fibers boast high transmittance, making them ideally suited for applications in the realm of decorative lighting, where their unique properties can be harnessed to create captivating visual displays.

In summary, the mechanical properties of polymer optical fiber directly influence its weaving capabilities. Additionally, the mechanical properties of the fiber after exposure to chemical reagents are also impacted, thereby affecting its weaving properties. Therefore, it is crucial to extensively test the mechanical properties of polymer optical fiber, particularly in the context of its weaving performance.

1) Technological parameters of multi-axial fabrics: In practical manufacturing, it is often observed that the rationality of the process arrangement for multi-axial warp knitted fabrics significantly influences the weft yarn structure within the fabric and the overall process flow. This can manifest in issues such as the weft yarn not being securely fixed within the ground weave or the fabric surface lacking weft yarn. These conditions often have repercussions on the tensile properties of the fabrics, as well as the mechanical properties of the composites post-molding. The weft-laying process primarily involves factors like fabric weight, weft yarn fineness, weft-laying angle, and the number of weft-laying layers. The processing parameters for multi-axial warp knitted fabrics encompass the fabric's gram weight, the gram weight of each weft layer, the density of each weft layer, the stitch pattern of the multi-axial fabric (i.e., the density of the stitching yarn), and the fineness of the stitching yarn and weave. The weight and density of the weft are determined by the weft laying process, which plays a pivotal role in the weaving of multi-axial fabrics. Unless there are specific requirements, the gram weight of each layer in a multi-axial fabric is typically calculated by dividing the total gram weight per square meter by the number of yarn layers [12, 13]. The weft density and fineness are key parameters in controlling fabric weight during the weft insertion process.

In actual production, the determination of these two parameters is mainly determined according to the weight per square meter required by customers. When producing axial warp knitted fabrics in more than two directions, when the total square meter gram weight of the fabric is given, the square meter gram weight of each layer of yarn must be determined first. The basis for the determination is that when the axial fabric is made into a composite material, without considering the force requirements in special directions, it is generally believed that only when the fabric as a reinforcing material has various similarities in structure, the composite material can jointly bear the load in all directions and exert the best performance of each component in the material [14, 15]. Therefore, when there is no special requirement, the square meter gram weight of each layer of yarn must be determined by dividing the total square meter gram weight by the average value obtained by the number of layers of yarn as a benchmark. After determining the weight of the next square meter, the specific process parameters are determined according to the calculation method of the weight of the square meter.

For example, in the actual production of biaxial fabrics, in order to make the force bearing capacity in the direction of 0° and 90° equivalent, generally under the condition that the square meter gram weight of the fabric is given, the square meter gram weight of the warp yarn and the square meter gram weight of the weft yarn are allocated according to half of the square meter gram weight of the fabric. Similarly, for multi-axial fabrics, if there are yarns inserted in directions other than 0° and 90°, such as: +45°, the forces in all directions should be considered to determine the yarn parameters [16, 17].

For warp-knitted axial fabrics, the parallel and straight alignment of yarns within the fabric structure ensures minimal fiber bending. As such, the calculation of the square meter gram weight for yarn in any layer direction of these fabrics is straightforward: simply multiply the gram weight of a one-meter-long yarn segment by the total number of yarns present within that one-meter length. This method accurately reflects the yarn content and density, crucial for assessing fabric quality and suitability in various applications.

III. Introduction to Reinforcement Learning

A. Basic Theory of Reinforcement Learning

Under the background of new power system construction, the participants of micro-grid are becoming more and more diverse, and the power generation output and load are in a state of random fluctuations, making the operating environment and mechanism more and more complex. The traditional energy management and scheduling methods are affected by the dynamics of the system and the intermittence of new energy sources, so it is difficult to establish an accurate mathematical model. Concurrently, it is imperative to estimate and fine-tune numerous parameters, encompassing load forecasting, energy supply, and price forecasting, among others. The computational complexity of these tasks is considerable, often rendering it challenging to fully satisfy the demands of practical scenarios. Furthermore, the majority of optimization challenges encountered in actual production processes are non-deterministic polynomial problems, posing certain difficulties in their resolution. Fig. 2 shows knit fabric quality changes over time.

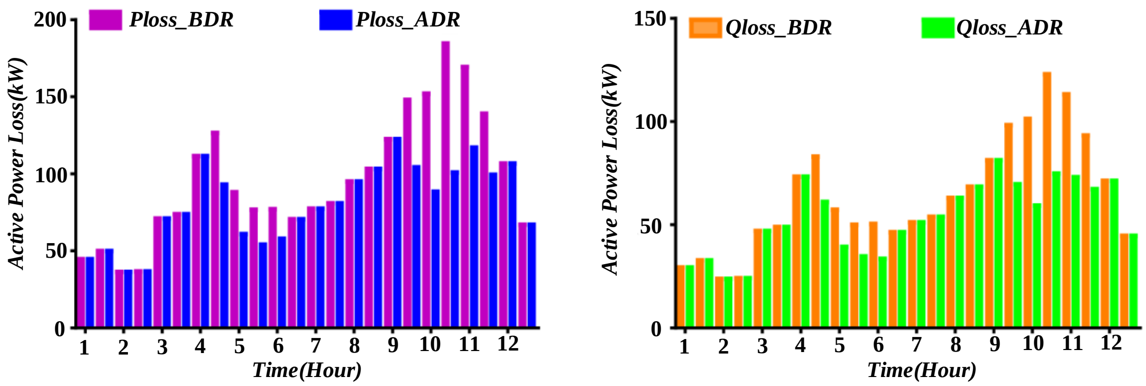

Fig. 2. Knit fabric quality changes over time.

Reinforcement learning evaluates the action based on the reinforcement signals provided by the environment, without determining in advance how the reinforcement learning system will form the correct action. Considering the limited information provided by the external environment, the reinforcement learning system must rely on its own continuous experience to continuously learn [18, 19]. Based on this model, reinforcement learning continuously acquires knowledge in an "action-evaluation" environment, and continuously optimizes action plans to adapt to the environment. The problems faced in the process of reinforcement learning have been widely discussed in biological learning, cybernetics, game theory and other fields. They are used to explain the equilibrium state under the condition of bounded rationality, and are also used to design intelligent interactive systems and unmanned adaptive systems. In recent years, reinforcement learning algorithms that integrate deep learning, transfer learning and other methods have the ability to solve complex problems in the real world, and have reached or surpassed the human level in many fields such as computer games, intelligence competition, automatic driving, intelligent question answering, and industrial production, showing extraordinary application prospects. With the continuous development of algorithms, its application range will become more and more extensive.

B. Technical Features of Reinforcement Learning

Reinforcement learning is known as the three major machine learning technologies together with supervised learning and unsupervised learning because of its powerful exploratory ability and autonomous learning ability. Compared with supervised learning and unsupervised learning, reinforcement learning has great differences in many aspects such as data acquisition, learning methods, and decision-making methods. Supervised learning has a clear label on each data sample, which corresponds to the reinforcement learning task, which means that every action that should be taken in a certain state has a clear label. This does not match the typical scenario of reinforcement learning. Unsupervised learning does not label the data, and the main purpose is to discover the distribution law of the data. Compared with unsupervised learning, reinforcement learning provides certain "labeling" (that is, reward signals), which can be regarded as a kind of weak labeling learning. Although this mark is a weak mark for a specific action, it is very clear for the entire learning task and directly marks the success or failure of the task. The decision-making process of reinforcement learning is continuous, and at each time step, the agent takes action through interaction with the environment and obtains reward signals. Reinforcement learning is a goal-driven active learning method, which generates learning samples through interaction between initiative and environment. In reinforcement learning, agents need to try new strategies to obtain higher rewards, and at the same time need to use known strategies to maximize known rewards. Therefore, how to improve the quality of interaction (exploration and utilization) is a key core of reinforcement learning. Exploration may lead to too many useless attempts, resulting in a large amount of resources being wasted, and too much use may miss better choices due to too much trust in current experience. However, due to the delayed nature of reinforcement learning rewards, agents must learn how to evaluate the long-term impact of current decisions, that is, actions made at current moments may affect rewards at multiple future moments [20]. Reinforcement learning usually does not require prior knowledge or environment models, which makes reinforcement learning very useful in dealing with unknown environments. Therefore, it has good scalability and adaptability, and can deal with problems such as multi-agent, uncertain and dynamic environments. Fig. 3 shows efficiency comparison before and after knitting path optimization.

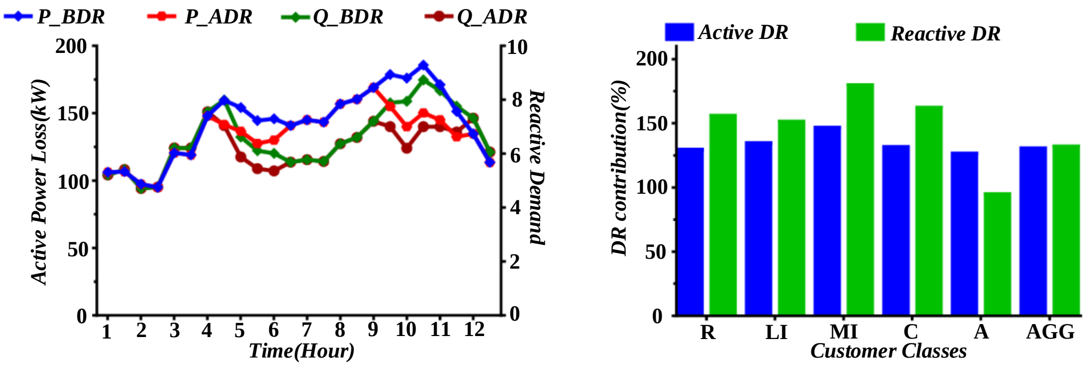

Fig. 3. Efficiency comparison before and after knitting path optimization.

Reinforcement learning embodies a continuous decision-making and strategy optimization process, leveraging intricate internal data structures and algorithms to maximize cumulative rewards through the dynamic interplay between agents and their environment. Initially, the agent engages with the environment guided by a formulated policy, observing and perceiving the current state of the environment after each interaction. Based on this state, the agent selects an action, triggering corresponding rewards or benefits. Over numerous interactions, the agent explores diverse action plans, gradually learning the optimal strategy for executing the most suitable action within a given environment, thereby maximizing overall gain. Presently, reinforcement learning encompasses three core methodologies: the value function algorithm, the policy gradient algorithm, and the "action-evaluation" algorithm, each contributing to the agent's capacity for learning and adaptability.

C. Algorithmic Flow of Reinforcement Learning

Reinforcement learning is widely used in model optimization in automatic control, engineering construction and other fields. Its core is that the agent can obtain the cumulative maximum return or achieve a specific goal through its own learning ability in the process of interacting with the environment, so that the agent has the ability to make the best decision under the current environment. In order to simplify the modeling problem of reinforcement learning, Markov decision process is used to describe and construct the process of reinforcement learning, considering the complexity of the transformation process between environments of reinforcement learning. Fig. 4 shows kit path optimization and model evaluation process.

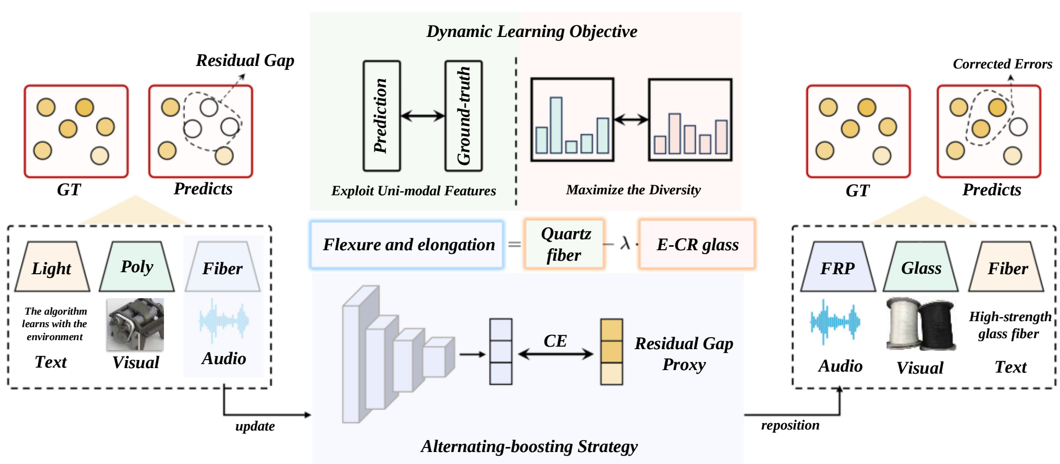

Fig. 4. Kit path optimization and model evaluation process.

Agent: A hypothetical entity that performs actions in an environment for some reward Environment: The scene in which the agent is located.

State: Refers to the current state returned by the environment

The goal of reinforcement learning is to maximize cumulative rewards, and future trends of rewards need to be considered when calculating rewards. Cumulative rewards are defined as the weighted sum of rewards from time t to the end of the learning process, represented as shown in Eq. (1).

$$R_t = \sum_{t'=t}^{T} Y^{t'-t_{rt}} \tag{1}$$

Where yE[0, 1] is a constant called the discount factor, used to assess the impact of future rewards on cumulative rewards. The state action function Q (s, a) represents the execution of action a in the current process and loops to the end of learning according to strategy π. The cumulative gain of the agent is shown in Eq. (2).

$$Q^{\pi}(s,a) = E[R_t \mid s_t = s, a_t = a, \pi] \tag{2}$$

Where s and a represent the current state and action. For all sets of state actions, if the expected returns of a strategy are greater than or equal to the expected returns of other strategies, the strategy is the optimal strategy. In fact, multiple optimal strategies may use the same state action function. Its mathematical expression is shown in Eq. (3).

$$Q^{*}(s,a) = \max_{\pi} E[R_t \mid s_t = s, a_t = a, \pi] \tag{3}$$

Meanwhile, the action function follows the Bellmann optimal equation to form the optimal state action function as shown in Eq. (4)

$$Q^{*}(s,a) = E_{s^{'} \sim s}[r + \gamma max Q(s^{'}, a^{'}) \mid s, a] \tag{4}$$

Where s denotes the subsequent state and a represents the action corresponding to *s*, the optimal value function can theoretically be derived through iterative application of the Bellman equation. However, in practical scenarios, due to the complexity of real-world environments, neural networks, linear functions, and other approximation techniques are frequently employed to estimate state-action value functions. This integration of deep learning and reinforcement learning not only enables the accurate approximation of intricate value functions but also fosters the rapid advancement and widespread adoption of reinforcement learning methodologies.

IV. Study on Tensile Properties of Multiaxial Fabric by Technological Parameters

In the actual production, it is often found that whether the arrangement of weft insertion and knitting technology of multi-axial warp knitted fabrics is reasonable or not will directly affect the structure of weft in the fabric and the progress of the process, such as causing the weft not to be well fixed in the ground weave or causing the fabric surface to lack weft. Because these conditions often affect the tensile properties of fabrics, this chapter mainly studies the effects of different production processes on the tensile properties of multiaxial fabrics from the perspective of weft laying and knitting processes through experimental testing methods [21]. The weft laying process mainly refers to the gram weight of the fabric and the fineness of the weft yarn, and the knitting process mainly refers to the weave structure, needle density, and let-off of the warp knitted yarn (bundled yarn). Because the multi-axial warp knitted fabric is a new material, there is no uniform standard about the performance test of the fabric. In this paper, the fabric tensile test is carried out by GB/T7689.5-2001 standard. The state transition probability formula and the reward function formula are shown in Eq. (5) and Eq. (6).

$$a_k = \frac{\exp(w^{\cdot}\ \tanh(Uh_k))}{\sum_{j=1}^{K}\exp(w^{\cdot}\ \tanh(Uh_j))} \tag{5}$$

$$r_k = \frac{\exp(v(x_k)/\tau_v)}{\sum_{k=1}^{K}\exp(v(x_k)/\tau_v)} \tag{6}$$

A. Methods and Conditions for Tensile Testing of Fabrics

Utilize an appropriate instrument to stretch fabric strips until rupture, thereby assessing their breaking strength and elongation at break. Both the breaking strength and elongation values can be directly discerned from the instrument's indicator device, or alternatively, derived from the automatically recorded stress-strain curve. Table I comprehensively outlines the pertinent test parameters employed in this analysis.

TABLE I. TEST PARAMETERS

	Unit	Sample parameter
Specimen length	mm	350
Width of specimen (unrimmed)	mm	65
Initial effective length	mm	200
Width of trimmed specimen	mm	50
Tensile speed	mm/min	100

In a humidity-controlled environment adhering to standard conditions of 23°C ± 2°C temperature and 50% ± 10% relative humidity, the sample undergoes a 16-hour humidity acclimation period. Subsequently, the testing is conducted in an identical environmental setting.

Based on the fabric type, adjust the upper and lower fixtures to achieve the desired effective length of the sample between them, ensuring they are parallel. Position the specimen in a jig with its longitudinal central axis aligning with the jig's leading-edge center. Cut cardboard or similar material along a direction perpendicular to the specimen's central axis. Apply a uniform pretension across the entire width of the specimen, and then securely tighten the other jig.

1) Start the movable fixture and tensile the sample until it is destroyed. The Q-value function update and policy gradient theorem formulas are shown in Eq. (7) and Eq. (8).

$$h(t, \overrightarrow{x_i}) = h_0(t)\eta(\overrightarrow{x_i}) \tag{7}$$

$$SA(z) = (\sigma(\frac{qk^T}{\sqrt{K_h}}))v \tag{8}$$

2) Record the final breaking strength. Unless otherwise agreed, when the fabric breaks in more than two stages, such as double-layer or more complex fabrics, the maximum strength at the break of the first set of yarns is recorded and used as the tensile breaking strength of the fabric.

3) Record elongation at break, accurate to 1 mm.

4) If a specimen is broken within 10mm of the contact line of either of the two fixtures, the phenomenon will be recorded, but the breaking strength and breaking elongation will not be calculated in the results, and the new specimen will be re-tested [22].

The reasons for coating resin on the clamping end are:

The surface of carbon and glass fibers is very smooth, and the direct clamping will cause slippage, which will affect the accuracy of the test. The value function iterations and the Bellmann equation formulas are shown in Eq. (9) and Eq. (10).

$$\mathrm{L} = \frac{2\sum_{i}^{N}\hat{p}_i y_i}{\sum_{i}^{N} p_i^{\;2} + \sum_{i}^{N} y_i^2} \tag{9}$$

$$S(e_i, e_{top-k}) = \frac{\sum_{m=1}^{M}(e_i \times e_{top-k})}{\sqrt{\sum_{m=1}^{M}(e_i)^2} \times \sqrt{\sum_{m=1}^{M}(e_{top-k})^2}} \tag{10}$$

The brittleness of carbon and glass fibers is large, and if the clamping force is too large, the sample at the clamping end will be damaged, making the glass fibers at the clamping end of the sample break first under the strong force, resulting in the phenomenon of breaking the clamping head, and then making the test invalid. After coating resin at both ends, the above problems can be effectively solved. The friction between the resin and the collet is much higher than that between the glass fiber and the collet, which effectively solves the problem of slipping. In addition, after coating the clamping end, the fibers in the clamping part are soaked in the resin. Under the protection of the resin, the glass fiber at the clamping end will be subject to a very small shear force, so that the problem of fiber brittleness can be effectively solved [23].

B. *Experimental Data Analysis*

In the tensile test, during the tensile load process of the fabric held by the clamp, the yarn in the fabric has obvious different breakage characteristics, which can be accurately judged from the sound produced when the yarn breaks. To some extent, the strength of the yarn in the fabric cannot be fully utilized in the process of application.

Fig. 5 shows reward changes during the iteration of reinforcement learning. The tensile strength of the fabrics with two different weave structures, No. 1 and No. 2, was tested in the direction of yarn 0. Five specimens were tested for each fabric. The action selection strategy and the advantage function calculation formula are shown in Eq. (11) and Eq. (12).

$$\mu_{0,\mathrm{crit}} = \frac{2}{(N+2)\sigma^2} \tag{11}$$

$$w_{k+1} = w_k - \frac{1}{2}\mu\nabla_k \tag{12}$$

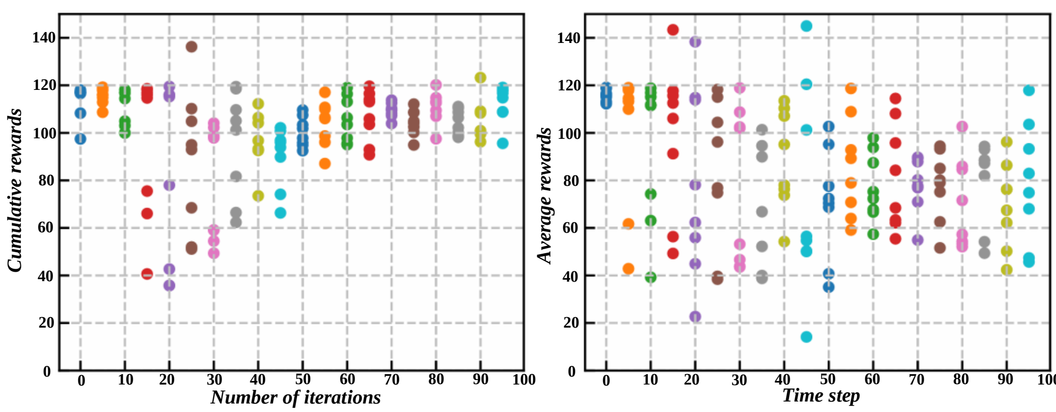

Fig. 5. Reward changes during the iteration of reinforcement learning.

It can be seen from the figure that the tensile properties of the fabrics with Promat as the weave structure are slightly higher than those of the same fabrics with tricot as the weave structure, and the difference in the tensile strength of the fabrics with tricot as the weave structure is small. Fig. 6 shows effect of learning rate on the effect of path optimization.

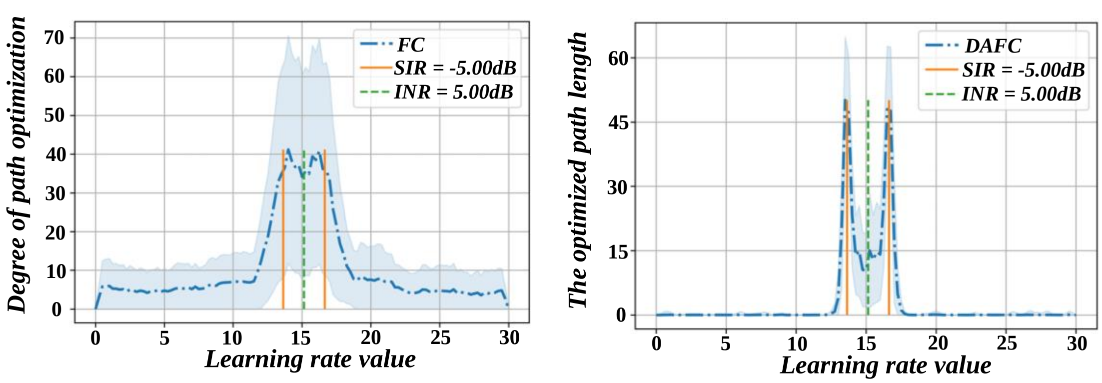

Fig. 6. Effect of learning rate on the effect of path optimization.

As depicted in Fig. 6, the fabric exhibiting the lowest stitch density boasts the highest average tensile strength. However, it is apparent that as the stitch density rises, the subsequent variations in tensile strength compared to this baseline fabric remain relatively modest. The results show that the increase of stitch density in the range of common stitch density increases the probability of fiber damage caused by needle penetrating yarn, but it has no obvious effect on the strength of fabric. Fig. 7 shows exploration-exploit the effect of trade-offs on pathway search.

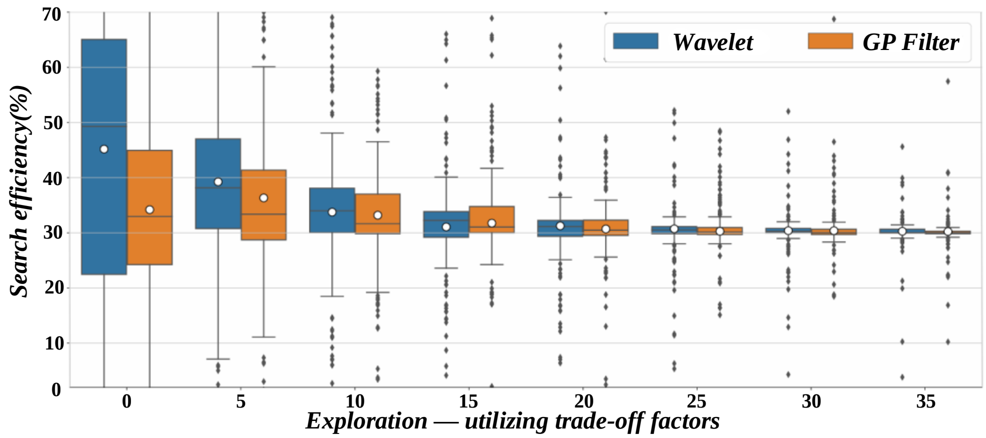

Fig. 7. Exploration-exploit the effect of trade-offs on pathway search.

As depicted in Fig. 7, the tensile strength of the fabric does not exhibit a regular pattern with variations in let-off amount. This is primarily attributed to the consistent weft insertion process and the maintenance of yarn count per unit length. Given the same stitch density, the likelihood of fiber damage within the yarn remains largely unchanged, resulting in insignificant variations in the fabric's ultimate strength. The target network update and knitting model are shown in Eq. (13) and Eq. (14).

$$\bar{n}_e = \frac{1}{a}\int_0^a n_e dr \tag{13}$$

$$x(t+1) = \bar{A}x(t) + \bar{B}u(t) \tag{14}$$

It is imperative to emphasize that warp-knitted yarn commands a premium price, thus, any augmentation in let-off volume directly correlates with an equivalent surge in costs. Conversely, maintaining excessively low let-off values introduces heightened tension within the yarn, which not only accelerates the wear and tear of knitting needles but also poses the risk of yarn breakage, ultimately hindering overall production efficiency. Therefore, for the actual production, we should choose the appropriate let-off amount [24]. The gradient descent optimization formula and the entropy regularization term formula are shown in Eq. (15) and Eq. (16).

$$(F * K)(q) = \sum_{s+t=q} F(s)K(t) \tag{15}$$

$$X_t^A = \frac{1}{C}\sum_{c=1}^{C} X_t(c) \tag{16}$$

C. Effect of Gram Weight of Fabric on Tensile Properties of Fabric

By increasing the gram weight of the 0° yarn layer, we measured the tensile strength of Fabrics No. 2 and No. 4 in the 0° direction. Specifically, Fabric No. 2 had a 0° yarn layer gram weight of 291.4 g/m2, while Fabric No. 4 boasted a gram weight of 582.7 g/m2. Notably, the gram weight of the 45° glass yarn layer remained unaltered, and all other process parameters were kept consistent. Fig. 8 shows optimize the comparison of before and after paths.

As Fig. 8 illustrates, as the fabric's gram weight increased, so did its breaking strength in the tensile direction. This phenomenon is primarily attributed to the increased density of the fabric, specifically the augmentation in the density of the 0° yarn. As the density of 0° yarns rises, the count of 0° yarns per unit length correspondingly increases. Consequently, when the fabric undergoes stress, the yarn's force-bearing capacity per unit area intensifies, ultimately contributing to a significant enhancement in the fabric's overall strength.

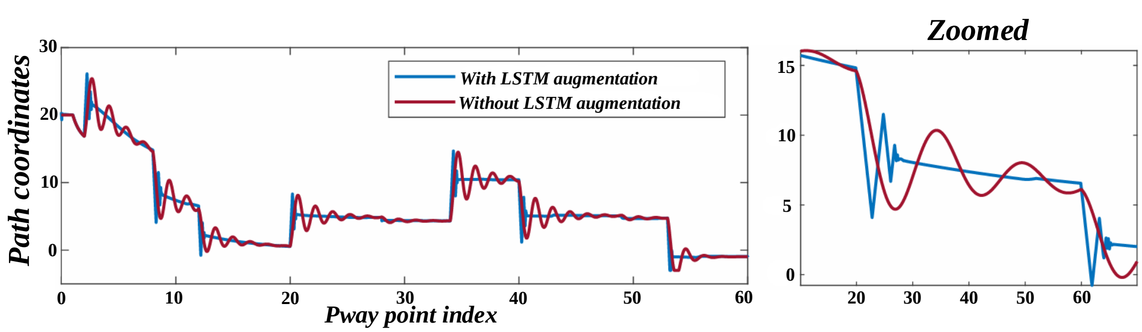

Fig. 8. Optimize the comparison of before and after paths.

By increasing the gram weight of the 45° glass fiber yarn layer, we measured the tensile strength of Fabrics No. 3 and No. 4 in the 0° direction. Specifically, Fabric No. 3 had a 45° yarn layer gram weight of 601.2 g/m^2, while Fabric No. 4's 0° yarn layer gram weight stood at 300.6 g/m^2. The gram weight of the 0° carbon fiber layer remained constant, and all other process parameters remained unchanged [25]. The importance sampling weights and discount factor influence formulas are shown in Eq. (17) and Eq. (18).

$$T_{N\varepsilon} = N\tau_Q + \sum_{i=1}^{N} \varepsilon_{c,i} \tag{17}$$

$$\sigma_t^2 = \frac{1}{2N-2} \sum_{i,j\neq i} \sigma_{ij}^2 \tag{18}$$

Fig. 9 shows effect of environmental state changes on path planning. As evident in Fig. 9, despite an increase in fabric gram weight, the breaking strength in the tensile direction experienced a marginal increase. The primary reason for this is that the 45° glass yarn does not significantly contribute to the tensile strength in the 0° direction. However, it does play a role in enhancing the fabric's pressure resistance and shares the load, thereby contributing to an increase in fabric strength, albeit not significantly.

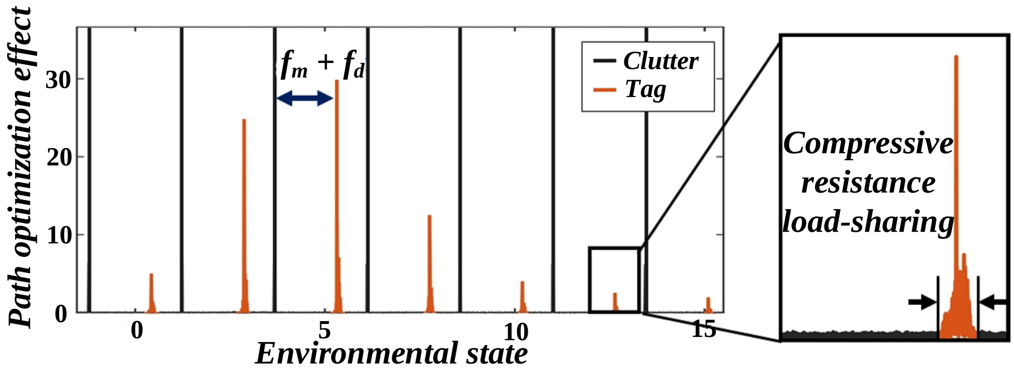

Fig. 9. Effect of environmental state changes on path planning.

At the same time, it can also be observed that the tensile strength of No. 3 fabric fluctuates very little while that of No. 4 fabric fluctuates greatly. The reason is that the weft density of No. 4 fabric is too small (4.5 ends/inch), resulting in uneven weft laying and lack of weft. If there is uneven weft laying in the fabric, if the sample is taken in the area of lack of weft during the experiment, the strength value obtained from the test should be low . If the sample is taken in the place where the weft is densely laid, the strength value obtained from the test is very high. As a result, the performance of different parts of the same fabric varies greatly. The multistep return estimation and model prediction error are calculated as in Eq. (19) and Eq. (20).

$$\mathrm{L}(q) = \ln \frac{p(x,\gamma,\lambda \mid y)}{q(x,\gamma,\lambda)}_{q(x,\gamma,\lambda)} \tag{19}$$

$$\hat{x}_i^H B_i \hat{x}_i = \sum_{l=1}^{d_l} \frac{|q_{i,l}|^2}{(1+\hat{\gamma}_i s_{i,l})^2} \tag{20}$$

With the fabric's weight kept constant, we varied the density of the 45° glass yarn and conducted tensile strength tests on Fabrics No. 4 (45° glass yarn density of 4.5 pieces/inch) and No. 5 (±45° glass yarn density of 2.25 pieces/inch).

Moreover, it becomes apparent that Fabric No. 5 demonstrates pronounced strength variations, primarily stemming from its exceptionally low weft laying density and irregular yarn positioning. This underscores the notion that, under consistent weight conditions, an increase in weft density fosters a direct enhancement in the fabric's tensile properties, as evidenced by prior studies.

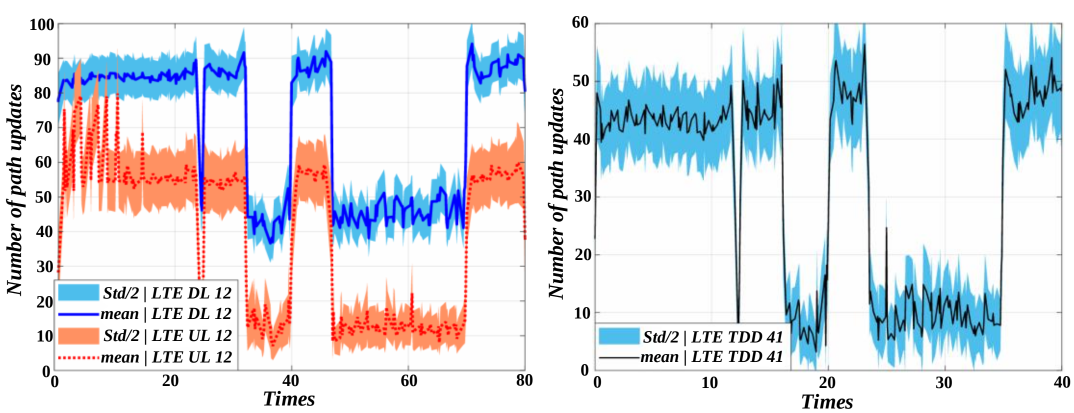

Fig. 10. Frequency of path updates during real-time learning.

However, it is worth noting that as the weft laying density increases, the linear density of the weft yarn decreases. Given that the current market prices of glass and carbon fibers rise as their linear density diminishes, it is imperative to comprehensively consider various factors, including fabric requirements, while setting the weft laying process to determine the optimal weft laying density. Fig. 10 shows frequency of path updates during real-time learning.

V. SUMMARY AND PROSPECT

With textile technology's advancement, flat knitting machines are crucial in the industry, with knitting efficiency and product quality as key performance metrics. Recently, reinforcement learning, an advanced ML technique, has been widely applied to optimization problems. This paper delves into utilizing Reinforcement Learning as a means to optimize knitting paths for flat knitting fabrics, with the ultimate goal of elevating both production efficiency and quality. The selection of knitting paths holds paramount importance, as it directly influences the aesthetic appeal, tactile sensation, and overall efficiency of the end product. Traditional optimization techniques, reliant on manual expertise and a cumbersome trial-and-error process, prove inefficient and inadequate for addressing intricate requirements. In contrast, RL facilitates the autonomous discovery of optimal paths through the dynamic interplay between the agent and its environment, thereby significantly advancing knitting efficiency and quality. We introduce an RL model specifically designed for optimizing knitting paths on flat knitting machines, meticulously defining state, action, and reward functions to capture the intricate nuances of the knitting process. By employing a reinforcement learning algorithm, our agent learns and explores within a simulated environment, progressively uncovering the optimal weaving path. Through a large number of experimental verifications, we prove that the knitting path optimization method based on reinforcement learning can significantly improve the knitting efficiency and product quality. In addition, the application effect of different reinforcement learning algorithms in knitting path optimization of flat knitting machine is discussed, and the key factors affecting the optimization effect are analyzed. We find that choosing appropriate algorithm parameters and reward functions is crucial to improve the optimization effect. Furthermore, we acknowledge the limitations of our current research and propose future directions for exploration. In summary, the reinforcement learning-based knitting path optimization for flat knitted fabrics holds immense potential. With continued research, we aim to further enhance knitting efficiency and product quality of flat knitting machines, ultimately contributing significantly to the textile industry's advancement.

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