Smart Innovation, Systems and Technologies 350

Xuesong Qiu · Yang Xiao · Zhiqiang Wu · Yudong Zhang · Yuan Tian · Bo Liu *Editors*

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Smart Innovation, Systems and Technologies 350

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Contents

Visualization Analysis of Research Hot Spots of Drug Patents in China

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Abstract. The purpose of the article is to provide references for the future development of drug patent field in China by analyzing the hotpots and trends thereof. The related articles of CNKI were retrieved with "drug patent" as the subject word and keyword, and visualized by CiteSpace software. The number of articles published in the field of drug patents is generally on the rise, and drug patent protection has become a research hotpots. The institutions and authors with high output concentrate on the innovation of drug patent system and the protection of intellectual property rights, which form three relatively close cooperation institutions; The main hot keywords are DRUG PATENTS, PATENT PROTECTION, BALANCE OF INTERESTS; Research on "drugs", "drug patents" and "safeguarding the legitimate rights and interests of patentee" has been formed. To protect the legitimate rights and interests of the patentee and promote the further reduction of drug prices.

Keywords: Drug patents · Patent system · CiteSpace

1 Introduction

Drug patents refer to patents applied for drugs, including drug product patents, drug preparation technology patents, drug use patents and other different types [1]. With the unprecedented development of science and technology and the development of reverse engineering, the research and development results of pharmaceutical enterprises are easy to be imitated at low cost, and the value of the disclosure of patented technology schemes decreases, so the demand for the protection of technical schemes by right holders is more urgent [2]. In recent years, drug patent protection has attracted much attention as an important means to promote the development and innovation of the pharmaceutical industry. On July 4, 2021, the National Medical Products Administration and the State Intellectual Property Office promulgated the *Implementation Measures for the Mechanism for the Early Settlement of Drug Patent Disputes (Trial)* (hereinafter referred to as the Implementation Measures). On July 5, 2021, the State Intellectual Property Office issued the *Administrative Decision on the Early Settlement Mechanism for Drug Patent Disputes* (hereinafter referred to as Administrative Decision), Meanwhile, the Supreme People's Court issued the *Provisions on Several Issues concerning the Application of*

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Law to the Trial of Civil Cases of Disputes over Patent Rights Related to Drugs Applied for Registration, which came into force today, marking the official implementation of the 1.0 version of China's drug patent link system [3]. Improvement of China's patent information registration system for Listed drugs. Academics see the field as one way to resolve various patent disputes and speed up the launch of generic drugs to the benefit of other companies and patients. In this study, CiteSpace software is used to analyze the relevant literature in this field, to discuss the trends and hot spots of this field, to provide reliable scientific basis for relevant researchers to explore the future development trend, and to provide reference for further research in this field.

2 Information and Algorithm

2.1 Literature Search

The literature related to the field of drug patents was searched in the CNKI database and the search time span from 2010 to 2021. After manual screening and software elimination of duplicates, 1031 articles are finally include, including 164 core journals, accounting for 15.9%.

2.2 Clustering Method

In this paper, CiteSpaceV software developed by Dr. Chen Chaomei is used to draw the knowledge map and keyword co-occurrence map based on the cooperation of authors, institutions, etc., and extract the author and keyword information of higher cited literature for analysis [4].

The algorithm formula is $LLR(b_i) = ln\frac{\mathrm{P}[b_i=0|\mathrm{y}]}{\mathrm{P}[b_i=1|\mathrm{y}]} = \frac{1}{\sigma^2}[min_{x:bi=1}\{|\mathrm{y} - \beta \mathrm{x}|^2\} - min_{x;bi=0}\{||\mathrm{y} - \beta \mathrm{x}||^2\}]$, and y is the input symbol to the de-mapper calculation; x is the QAM constellation points; β(BETA) is the constellation energy; $\frac{1}{\sigma^2} = 1/NV$ (Noise Variance Inverse-NVI).

Consider two random variables X and Y whose joint probability density function is p(x, y) and whose marginal probability density functions are p(x) and p(y), respectively. The mutual information I(X, Y) is the relative entropy between the joint distributions p(x, y) and p(x)p(y).

$$KLD = D(p|q) = \sum_x p(x)\log\frac{p(x)}{q(x)} = E_p \log\frac{p(x)}{q(x)}$$

p and q are two probability distributions.

$$MI = I(X;Y) = \sum_X \sum_Y p(x,y) log\frac{(x,y)}{p(x)p(y)} = D(p(x,y)\|p(x)p(y))$$

$$I = (X;Y) = H(X) - H(X|Y) = H(Y) - H(Y|X) + H(X) + H(Y) - H(X,Y)$$

The LSI is based on the singular value decomposition (SDV) method to obtain the article topic. Te SDV decomposition can be approximated by writing: $A_{m*n} \approx U_{m*k}\Sigma_{k*k}V_{k*n}^T$.

Applying the above equation to the topic model, SDV can be interpreted as follows: input m texts with n words in each text. $\mathbf{A_{ij}}$ corresponds to the feature value of the **j**th word in the **i**th text, commonly based on the preprocessed is normalized TF-IDF value. **K** is the assumed number of topics, generally less than the number of texts. After SDV decomposition, $\mathbf{U_{il}}$ corresponds to the relevance of the **i**th text and the **l**th topic; $\mathbf{\Sigma_{lm}}$ corresponds to the the correlation between the **I**th topic and the **m**th word sense; $\mathbf{V_{jm}}$ corresponds to the correlation between the **l**th word and the **m**th word.

Generally, the clustering effect of the atlas is measured according to the clustering modularity index (Q value) and the clustering contour index (S-value), and the larger the value, the better the clustering effect of the network. When the Q value exceeds 0.3 and the S value is greater than 0.5, clustering is considered reasonable.

In terms of literature volume prediction, the former Soviet scientists Narimov and Freidutz believed that the literature could not grow indefinitely. Based on the research, a logical curve growth law of the literature was proposed, whose mathematical formula is $f(t) = \frac{k}{1+ae^{-bt}}$.

$f(t)$ is t-years of literature accumulation; k is Literature cumulative maximum; a is Parameters; b is continuous growth rate of the literature; t is time.

3 Results

3.1 Distribution of Posting Time

We can quickly understand the overall evolution status of the feld through the publication number of documents. Figure 1 shows the changes in the number of publications on drug patent during 2010–2021 (2022 is the predicted, the data from China Knowledge Network). Generally, the publication trend is gradually increasing. In detail, we can see that from 2010 to 2013,the number of relevant research papers has not increased or even decreased, the average number of papers issued is 72; From 2014 to 2017,the number of relevant research was stable, with an average annual number of 59. The rapid development stage is 2018–2021, with an average annual number of 114 documents. This trend indicates that more scholars have paid extensive attention in drug patent as time elapsed. Therefore, it is reasonable to believe that the research in drug patent will fourish in the future, and more scholars will participate in this domain.

3.2 Author Distribution and Co-Linear Network

Figure 2 shows the network map of authors' cooperation in drug patent research. The results show that there are 344 nodes, 98 connections, and the network density is 0.0017. Observing Fig. 2, it is apparent that many authors tend to collaborate with a relatively stable group of collaborators to generate several major author clusters, and each cluster usually contains two or more core authors. Figure 2 demonstrates that the most representative author in the field is Jingxi Ding, Rong Shao and Jiejing Yao,etc.

Table 2 lists the top 10 most frequently cited literature authors. Learning relevant experience from abroad to promoting the establishment of China's drug patent linkage system [5–7] and the protection of drug patent intellectual property rights [8, 9] are the main research contents.

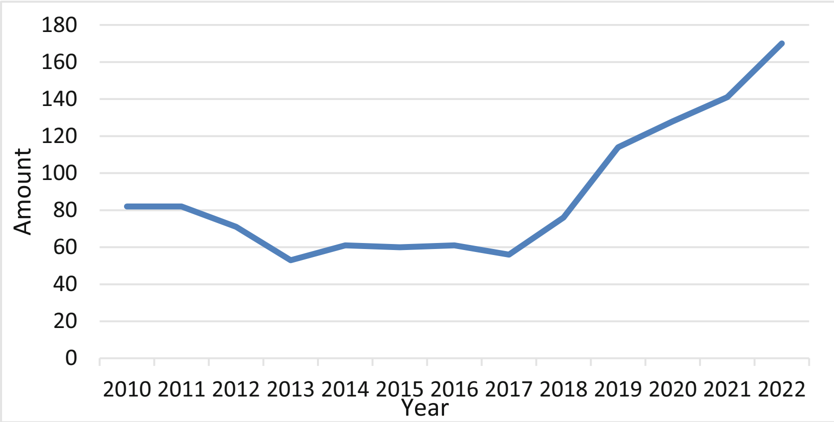

Fig. 1. Publication trends on drug patent (2000–2022)

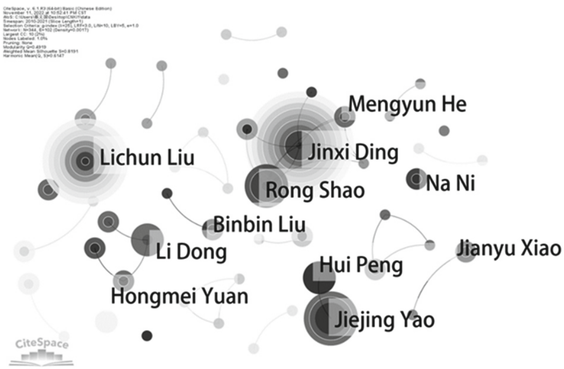

Fig. 2. Author collaboration network

According to Price's law [10], the minimum value of core journal authorship is $N = 0.749 \times \sqrt{Npmax}$ (Npmax is the highest yielding authorship)The top 10 core authors and their units and number of publications in this study are shown in Table 1. It can be seen from the table that Jinxi Ding, the most prolific author, has published 9 articles.This gives a minimum value of $N = 0.749 \times \sqrt{9} = 2.247$ for the number of core author publications in this study.The minimum number of articles issued by core authors is two according to the upper limit is rounded. 136 core authors, 164 papers accounting for 15.9% (50%) of all papers in the field.

3.3 Institution Distribution and Co-Linear Network

Figure 3 shows the academic cooperation among diferent institutions in drug patent research. The fgure is composed of 277 nodes and 98 cooperation links and the network density is 0.0014. It can be seen that the network density of the atlas is low, and the cooperation between the author's organizations is not close. In terms of node size, China

Table 1. Top10 core authors in the field of pharmaceutical patent research in China

Core Authors	Institution	Number	Core Authors	Institution	Number
JinxiDing	China Pharmaceutical University	9	XiaoxiaoHu	Central South University of Forestry Technology	3
LichunLiu	China Pharmaceutical University	7	HongmeYuan	Shenyang Pharmaceutical University	3
RongShao	China Pharmaceutical University	4	HuaHe	China Pharmaceutical University	3
LiDong	Shenyang Pharmaceutical University	3	XuezhongZhu	Tongji University	3
KanTian	Nanjing University of Chinese Medicine	3	YuanjiaHu	University of Macao	3

Pharmaceutical University, Shenyang Pharmaceutical University, East China University of Political Science and low and China University of political and law has the most significant node size, most of them are cooperation between colleges and universities.

3.4 Keyword Co-occurrence Analysis

Figure 4 shows the knowledge network of co-occurred keywords, which consists of 364 nodes and 654 connections. We can fnd that the current popular keywords in this feld include “pharmaceutical patents”, “public health”, “compulsory licensing”, “generic drugs”, “patent links”, “balance of interests”, “patent protection”, and “patent law”.

In detail, Table 3 lists the most frequently co-occurred keywords in terms of frequency, centrality, and year of occurrence. The top co-occurred keywords are “Pharmaceutical patents” (254 times), “Public Health” (130 times), and “Compulsory licensing” (125 times), “Generic Drugs” (107times). The keywords “Pharmaceutical patents”and“Public Health”are most frequently manily because drug patents protect the interests of drug developers and give them more incentive to develop new drugs to help the public escape health crises.

3.5 Keyword Clustering Analysis

The purpose of cluster analysis is to understand the research hotspots in the field and is based on keyword co-occurrence networks. The results showed that the keywords studied in this field were clustered into 9 categories, which is displayed in Fig. 5, and the sub-categories were #0 generic drugs, #1 drug patents, #2 patents, #3 patent protection, #4 compulsory licenses, #5 intellectual property rights, #6 patentees, #7 patented drugs,

Table 2. Top 10 most cited references of drug patent research

Number	Title	Author	Periodicals	Year	Frequency
1	Transplantation and Creation of Pharmaceutical Patent Linkage System	Zhiwen Liang	Politics and Law	2017	80
2	TRIPS-PLUS protection for pharmaceuticals in U.S. free trade agreements	Zhiwen Liang	Comparative Law Studies	2014	65
3	The Expansion of TRIPS-PLUS Clause and China's Response Strategy	Xueyan Wu	Modern Jurisprudence	2010	62
4	Application of Compulsory Licensing System for Pharmaceutical Patents in Developing Countries	Ming Hao	Intellectual Property	2015	59
5	Protection of Intellectual Property Rights in International Trade in the Context of Economic Globalization	Chao Fan	Journal of Northeast University of Finance and Economics	2011	57
6	Challenges and Responses: The Future of China's Pharmaceutical Patent System	Meili Wang	Intellectual Property	2017	57

(*continued*)

and #8 patent infringement, and some of the tag words for this cluster are shown in Table 4.

Figure 5 shows the keyword co-occurrence clusters in drug patent research.This clustering profile has a significant structure and reasonable clustering with a Modularity value of 0.4919 (>0.300) and a Silhouette value of 0.819 (>0.500) [11]. Generally, we can fnd that the keywords cover various topics, such as the aspect of drug ("#0, #1, and

Table 2. (*continued*)

Number	Title	Author	Periodicals	Year	Frequency
7	The Selection of Elements of Drug Patent Linkage Systems in the United States and Canada and Their Implications for China	Lichun Liu	China Science and Technology Forum	2014	56
8	Research on the development rules and policies of biomedical industry	Jianchong Wang	Journal of Huazhong Normal University	2011	55
9	A Study of the U.S. Drug Patent Linkage System	Jin Chen	Chinese Journal of New Drugs	2012	52
10	Exploration of the establishment of a patent linkage system for pharmaceuticals in China	Yongshun Chen	Technology and Law	2018	51

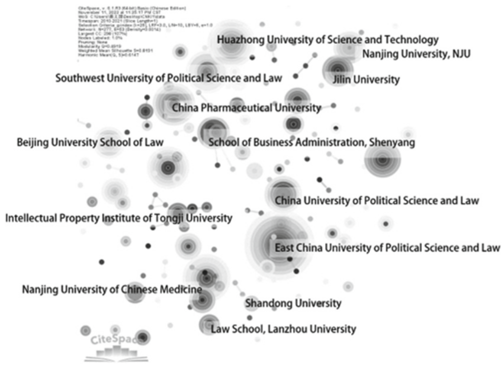

Fig. 3. Institution collabration network

#7"), drug patent rights("#2, #3, and #4"), ("#5, #6 and #8")are mainly for the protection of the legitimate rights and interests of the patentee and the protection of intellectual property rights.

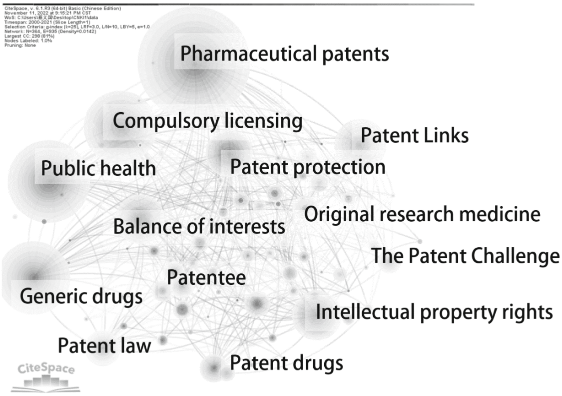

Fig. 4. Keyword co-occurrence network

Table 3. The top 10 keywords in terms of frequency

Nnmber	Keywords	Frequency	Centrality	Year
1	Pharmaceutical patents	254	0.34	2010
2	Public Health	130	0.14	2010
3	Compulsory licensing	125	0.12	2010
4	Generic Drugs	107	0.19	2010
5	Drugs	70	0.17	2010
6	Patent Links	69	0.11	2010
7	Balance of interests	63	0.12	2010
8	Intellectual Property	54	0.2	2010
9	Patent Protection	49	0.14	2010
10	Patent Law	33	0.1	2010

3.6 Analysis of Emergent Words

The citation burst of keywords reflects the changes in hotspots and the emerging trends of topics in a particular research feld. As shown in Fig. 6, this study selects 20 keywords with high burst intensity in the drug patent field.

Table 4. Keyword clustering information

Cluster Number	Frequency	Cluster name	Centrality	Clustered sub-clusters
#0	48	Generic Drugs	0.86	Patent Links, Pharmaceutical Patent Protection, Listed drugs
#1	48	Pharmaceutical patents	0.733	Drug Accessibility, Pharmaceutical patents, Rationalization of technical effects
#2	41	Patents	0.858	Compulsory licensing, Public Health, Drug Accessibility
#3	39	Patent Protection	0.84	Intellectual Property Protection, Patent Protection, Reverse Payment Agreement
#4	35	Compulsory licensing	0.695	Compulsory licensing, Patent evergreening, Public Interest
#5	32	Intellectual Property	0.824	Pharmaceutical patent rights, Patent measurement, New Drug Research and Development
#6	31	Patentee	0.874	Patent protection duration, Intellectual Property Enforcement, Intellectual Property Agreement
#7	17	Proprietary drugs	0.897	Centralized Purchasing, Price negotiation mechanism, Innovative Drugs
#8	7	Patent Infringement	0.951	Principle of Equivalence, Patent Infringement, Technical Basis

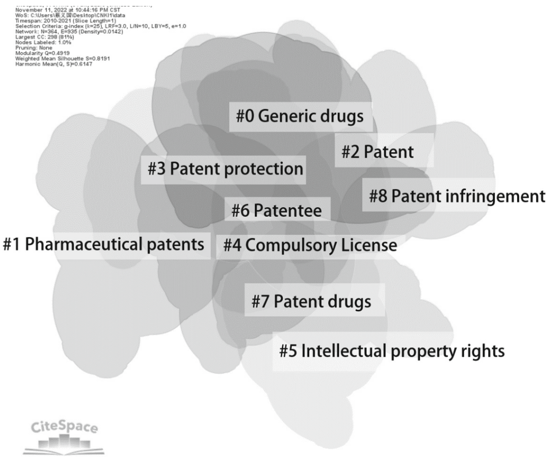

Fig. 5. Keyword cluster network

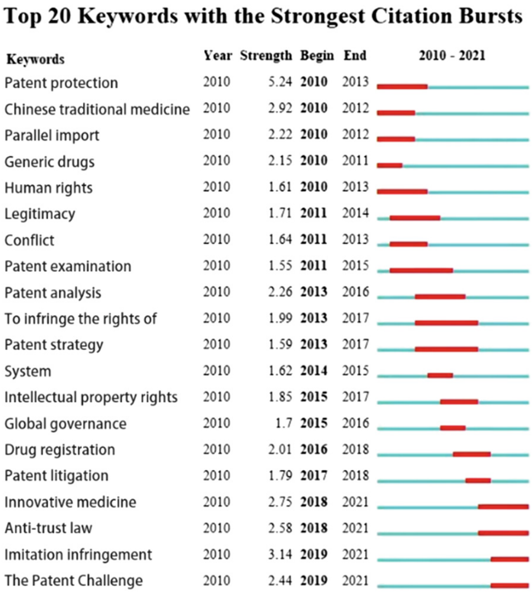

Fig. 6. Top 20 keywords with the strongest citation bursts

4 Conclusion

4.1 Literature Characterization

The authors agree that the network map presents an unstable core group of authors, and the number of individual publications of core authors is low, and there is a lack of in-depth research. In the distribution of author institutions, the scale of cooperation between institutions of higher learning and other institutions is relatively limited, and the cooperation between relevant authors and other institutions can expand the cooperation network.

The results of keyword co-occurrence network showed that “drug patent” and “public health” had large nodes and high centrality, followed by “generic drugs”. This is because the development of medicines is linked to public health issues and in many developing countries has a direct impact on the public’s access to necessary treatment and health services[12]. Imitation is a strategy for Chinese pharmaceutical enterprises to develop new products in the present and even in the future for a long time, and this way of R&D is the most likely to produce patent disputes[13]. However, the keywords such as “patent law” and “patent protection” appear less frequently, indicating that there are few legal and regulatory research levels in this field.

Combined with 9 key words clustering group and each cluster sub-cluster, the research content in this field is differentiated significantly, involving drug patent system, drug price, patent protection and other aspects.

Through the emergence graph of high-frequency keywords, it can be seen that the research hotpots have changed from the large scope of patent protection and patent analysis to the more detailed aspects of patent link, anti-monopoly law, patent challenge and data protection, so as to balance the interests of original pharmaceutical enterprises, generic pharmaceutical enterprises and public health.

4.2 Research Hotspots and Trends

Patent protection is a hot spot for research. At present, there are problems such as insufficient legislation on pharmaceutical intellectual property rights, difficulties in judicial handling of infringement cases, and inconsistency between authorization standards and infringement standards in China [14]. Solving the above problems is of great significance to strengthen patent protection and safeguard the interests of original drug enterprises, which is a study of patents from the perspective of original drug pharmaceutical enterprises.

The balance of interests is a hot topic that continues to rise. 2019 to 2024 is the second global drug patent cliff”, and a large number of drug patents will expire [15]. Many generic drug companies will take advantage of the opportunity to seize the market to gain more benefits. The emergence of the drug patent linkage system will not only avoid patent infringement, but also reduce the waiting period for generic drugs to be marketed, which will benefit generic companies and patients.

Patent challenges and anti-monopoly are the future research trends in this field. On the one hand, it is to reduce the monopolistic behavior of pharmaceutical giants and allow a large number of generic drugs to enter the market in order to reduce drug prices. On the other hand, it is to stimulate the original drug companies to innovate continuously to produce drugs with better efficacy and fewer adverse reactions.

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Ceramic Tile Production Intelligent Decision Research Based on Reinforcement Learning Algorithm

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Abstract. Ceramic tile production includes a complex decision system, which involves several intelligent decision acts and might affect the product quality. In general, traditional ceramic tile production utilized many repeated empirical experiments based on their engineers to determine an appropriate production parameter and pursue the desired product quality. However, it is observed that traditional ceramic tile production mainly depends on empirical experiments and couldn't ensure a stable product quality. Moreover, the various surrounding environments for ceramic tile production might further result in a worse product quality when the empirical production parameters determined by empirical experiments couldn't be adjusted by the actual situation. To solve the issue that empirical production parameters determination in the traditional ceramic tile production, a ceramic tile production intelligent decision framework is firstly designed based on reinforcement learning algorithm (i.e., Deep Q-networks (DQN)) in the paper. In the framework, both environment and agent modules are built, where environment module is designed to simulate various surrounding environments for ceramic tile production and then predict the corresponding product quality in time by a self-prediction random forest (RF) model. In addition, agent module aims to rapidly adjust the production parameters adaptively based on the predicted product quality to achieve a desired final product quality. The experiment results indicate that proposed ceramic tile production intelligent decision framework could effectively solve adaptive production parameters determination issues in the practice.

Keywords: Prediction model · Reinforcement learning · Ceramic tile production · Production parameters

1 Introduction

The ceramic tile production industry is an important construction-related industry. China, as the world's largest producer, consumer, and exporter of ceramic tiles, has driven global expansion by sheer volume. However, the production of ceramic tiles is a fairly complex process involving numerous operating sessions and several production parameters (a

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brief example is provided in Fig. 1, where equipment and production parameter include several variables). In general, the production parameters mostly rely on expertise and experience and have been determined through trial-and-error which results in uncontrollable product waste. Therefore, establishing an intelligent decision-making framework for ceramic tile production that overcomes the limitation of empirical is necessary.

As the production of ceramic tiles involves several phases, the correlation between production parameters and product performance is typically complex and ambiguous. In previous studies, fuzzy systems [1] and expert systems [2] were used to optimize the production parameters for ceramic tiles based on production data and human expertise. Currently, machine learning is commonly used to optimize the parameters automatically by computer algorithms. Deng et al. [3] used an orthogonal experiment design and back-propagation artificial neural networks (BP ANNs) to investigate an alumina slurry with excellent extrusion and shape retention properties. Ahmmad et al. [4] applied Random Forest (RF) to predict the density of novel oxy-fluoro glasses based on their chemical composition and ionic radii which acquired the highest R^2 compared with other Artificial Intelligence techniques. Similarly, Mu et al. [5] reported that artificial intelligence-aided is effective in the identification of ancient Chinese ceramics. There are some intelligent algorithms used in other related industries, but due to the more phases and great uncertainty in the ceramic production process, they are less used in ceramic production.

In industry 4.0 era, the processes of ceramic tiles manufacturing involve many production parameters. It is significant for us to search optimal production parameters among the huge searching space and thus achieve a desired product quality. The traditional methods either simplify certain insignificant details or require prior expert knowledge and manual intervention that results in not dealing with those problems flexibly among the huge searching space. The process of searching the optimal production parameters setting can be modeled as a Markov decision process, and reinforcement learning (RL) [6, 7] can effectively learn the optimal decision of the Markov decision process in high-dimension searching space that has been broadly used to tackle the practical optimization and decision-making problem in the industry. For example, in [8], the renewal price adjustment problem in the insurance industry was modeled as a sequential decision problem in terms of a Markov decision process (MDP), and the revenue is optimized subject to customer retention by the RL algorithm. Han et al. [9] used a proximal policy optimization algorithm in RL to construct an intelligent decision-making model for pavement maintenance plans, which could be applied to the increasing demand for pavement maintenance. The authors of [10] have applied dueling based deep reinforcement learning to optimally dispatch the household energy management system (HEMS). Guo et al. [11] employed a RL framework and a self-prediction artificial neural network model to approach the narrow process windows problem and could produce ultra-high precision products. He et al. [12] constructed a framework that transformed the textile process optimization problem into a stochastic game, and used a deep Q-networks algorithm to achieve the optimal solutions for the textile ozonation process in a multi-agent system. Related applications of RL for decision-making have been reported. However, at present, there is no complete study to solve a complex production parameters adjustment issue, especially in the ceramic tile manufacturing industry.

Inspired by the above methods, process parameter optimization is considered as a highly dynamic and complex decision-making process in ceramic tile production. This study aims at developing a decision-making framework for optimizing the ceramic tile manufacturing process based on RL. The key contributions of this paper are summarized as follows:

(1) Design a reinforcement learning-based production parameters optimization framework for the ceramic tile manufacturing process.
(2) Train self-prediction quality model. Establish a RF prediction model that can map the complex relationship between the production parameters and product quality by using the background data. Then employ the trained RF prediction model as a part of the environment module.
(3) Train RL decision model. Build and train a decision model for learning production parameter adjustment strategies through a reinforcement learning algorithm. The reinforcement learning agent would be trained by interacting with the environment.

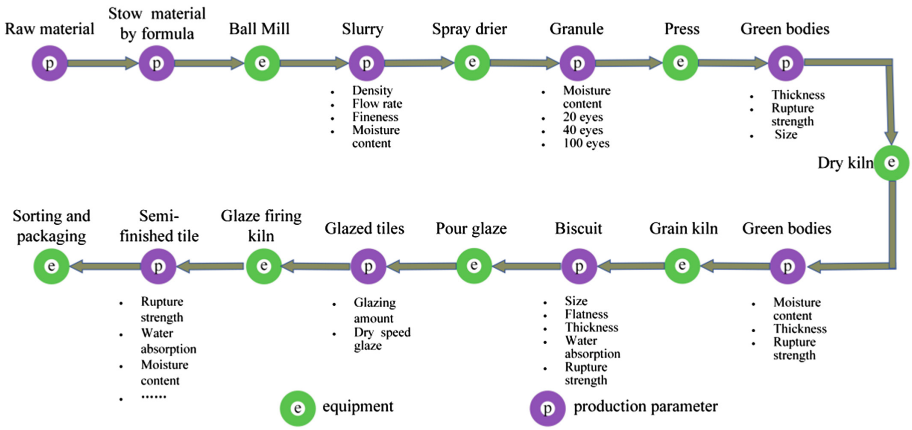

Fig. 1. The complete flow diagram for the ceramic tile production

2 Literature Review

2.1 Artificial Intelligent Techniques

In recent years, researches regarding predictive models based on various regression approaches or machine learning algorithms, such as support vector machine, artificial neural network and random forest have be used in many industries. Support vector machine is a popular machine learning tool for classification and regression, the excellent use of support vector machine in textile industry has been issued for predicting yarn properties [13]. In this study, high volume instrument and advanced fiber information system fiber test results consisting of different fiber properties are used to predict the rotor spun yarn strength. Cassar et al. [14] designed and trained an artificial neural network in predicting glass transition temperatures for more complex oxide glasses. A previous study [15] comparing the random forest with other machine learning to predict the T_g of glasses based on their chemical composition. The results show that the best machine learning algorithm for predicting T_g is the random forest. In this paper, the attempt of modeling the ceramic tile production process by the application of the three artificial intelligent techniques is conducted. The predicted models were constructed with corresponding optimization process to comparatively find the potential applicability of them in predicting the product performance of the ceramic tile production process. The model with fine prediction performance will be used to build the environment module of reinforcement learning. The model was realized by using the Scikit-learn library in Python 3.7.

2.2 Deep Q-networks Reinforcement Learning Algorithm

As an effective artificial intelligence method, reinforcement learning has been widely applied to deal with decision-making issues in various fields [16, 17]. Thus, this article uses DQN as a decision algorithm. The primary components of reinforcement learning are the autonomously learning agent module and the external environment module.

We used a typical reinforcement learning algorithm policy-based learning (DQN) [21] to solve the decision optimization problems. Different from some basic reinforcement learning algorithms is the special agent module. In order to address the dimensionality challenges of Q-learning [18], the DQN method employs a DNN in agent module, parameterized by θ, which takes as input a continuous state s_t and outputs an estimate of the Q-value function (i.e. $Q(s_t, \mathrm{a}_t) \approx Q_\theta(s_t, \mathrm{a}_t)$) for each discrete action. When agent learns the optimal strategy, the agent's decision in terms of which action A_t is chosen at a certain state S_t is driven by a policy $p(S_t) = A_t$. The agent changes its strategy for selecting actions based on the action's maximal value. At this time, the environment gives the agent a feedback reward $\mathrm{R_t}$ based the action's effect, and the environment reaches a new state S_{t+1}, then the agent repeats the above operations. The environment's state $s \in S$, where S is a finite set, similarly, $\mathrm{a} \in A$ and $r \in R$.

Considering the dynamic optimization procedure in ceramic tile production is a sequential decision problem that can be modeled as a Markov Decision Process (MDP). The MDP can be solved by reinforcement learning (RL) [22].

3 Proposed RL Framework in This Study

Figure 2 depicts the main structure of proposed RL framework, where the decision-maker acts as the agent to traverse and explore the state space in environment module, i.e., the different production parameters situations in ceramic tile production process. The environment module mainly consists of a pre-trained prediction model, and the adjustment of production parameters denotes the action. When RL framework optimizing production parameters, the agent module takes action on a state (production parameters) in the environment module and the environment transform the state to a new state, then prediction model take new state as input and output the variables (product quality). The variables are used to calculate the reward by designed reward function.

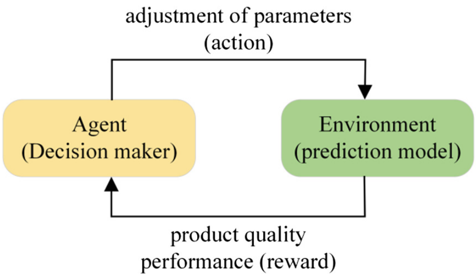

Fig. 2. The main structure of proposed RL framework

3.1 Problem Formulation

In this Subsection, we defined some parameter variables. The $\{pv_1, pv_2 \cdots pv_n\}$ is defined to denotes the production parameters in ceramic tile manufacturing process, while the multi-criteria of $\{c_1, c_2 \cdots c_n\}$ denotes the product quality corresponding to product parameters. Decision-making system in this paper needs to figure out how those parameter variables affect the product quality in terms of each criterion, and whether a solution set $\{pv_1, pv_2 \cdots pv_n\}$ is good or not relating to $\{c_1, c_2 \cdots c_n\}$, the product quality performance of the specific solution could be presented by:

$$f_i(pv_1, pv_2 \ldots pv_n)|c_i, for\ i = 1, \ldots m \tag{1}$$

When the domain of $pv_i \in PV_j$ is known, and the multi-criteria $\{c_1, c_2 \cdots c_m\}$ problem could be somehow represented by C, and the Eq. (1) could be simplified to (2), and so that the objective of decision-makers is to find (3):

$$f(pv_1, pv_2 \ldots pv_n)|C, pv_j \in PV_j \tag{2}$$

$$\text{argmax}_{pv_j \in PV_j}[f(pv_1, pv_2 \ldots pv_n)|C] \tag{3}$$

The objective of Eq. (3) is to find the optimal solution of variable settings, whereas prior operations in traditional ceramic tile production depended mainly on trial and error. Subsection 3.2 and 3.3 describes in detail how to utilize the RL model in the ceramic tile production decision-making.

3.2 Prediction Model

The application of prediction model in proposed decision-making framework is divided into two steps:

(1) Pre-trained the prediction model: a prediction mapping model could be built to predict the output corresponding to the input after the experience data are obtained. The model in this paper would be used to predict the quality characteristics under different process parameter conditions. The machine learning library of Scikit-learn is employed to develop the prediction models [22].

Prior to the experience data being fed to the prediction model, it should be pre-processed. The production parameters $\{pv_1, pv_2 \cdots pv_n\}$ and corresponding process response/outputs $\{c_1, c_2 \cdots c_n\}$ be processed by using the train_test_split function of scikit-learn, the data is split into training and test sets. A test size of 0.2 for all the experience data was fixed, it shows we could use 20% of the data for testing ensuring maximum reproducibility. The construction procedure is described below, and a forecast flow chart is shown in Fig. 3.

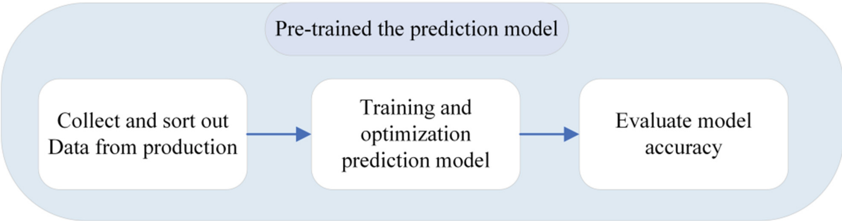

Fig. 3. The construction process of the prediction model

We demonstrate the process optimization method to improve the performance of ceramic tiles by considering a small subset of the process variables. This model later can be extended to encompass all relevant parameters. The two prediction models we established adopted two parts of data respectively. The one production parameters data come from multi-process (Spray drying, Press, Kiln), and the other from Single-process (Spray drying).

(2) Employ the trained prediction model as a part of the environment module: After comparing the prediction performance of support vector machine, artificial neural network and random forest prediction models. The random forest (RF) predictive model, constructed using Multivariate Random Forest (MRF) [23] in which a sample input has more than one target output, is applied to simulate the ceramic tile production process in the proposed framework.

3.3 DQN for Ceramic Tile Production Decision

The ceramic tile production decision RL model based on DQN is presented as follows. Figure 4 illustrates the framework for the proposed decision model to address our problems, which would be attempted to solve the performance quality optimization problem of the spray drying process.

In our scheme, the agent continuously interacts the values/parameters with the environment module, which feedbacks the rewards to the agent. Through cumulative rewards, the agent is expected to learn to control the process parameter of the spray drier in order to meet the production granule performance that minimizes the difference between such specific process treated granule product and the targeted sample performance.

In this paper, the decision-making problem is modeled as an MDP, which consists of a tuple of five elements (S, A, T, r, γ). Where T is a state transition probability function $T(s_{t+1}|s_t, a_t)$. The details of those elements are described as follows:

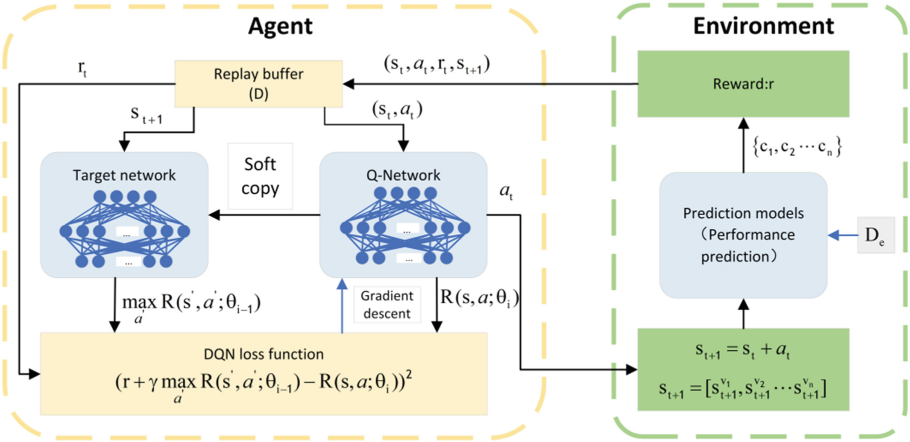

Fig. 4. Workflow of the algorithm implementing the proposed DQN method for ceramic tile manufacturing process optimization.

State space S: A state space $s_t \in S$ in this case is composed by the solutions with four production parameters (burning temperature, inlet air temperature, exhaust temperature, temperature of the tower), which is the input parameters $\{pv_1, pv_2 \cdots pv_n\}$ of the prediction model in environment module. It is described as $S_t = \{s_t^{pv1}, s_t^{pv2}, s_t^{pv3}, s_t^{pv4}\}$, where $s_t^{pv_k}$ is the current value of the kth process parameter.

Action space A: An action that recommends an adjustment amount of the production parameters based on the current s_t, is denoted as $A_t = \{a_t^{pv1}, a_t^{pv2}, a_t^{pv3}, a_t^{pv4}\}$. The four corresponding production parameters are controlled by the agent within the constraints. As the action of a single variable pv_k could be kept as 0 or adjusted in the given range with specific unit u, where $a_t^{pv_k} \in \{-u_k, 0, +u_k\}$.

Transition function P: The transition function maps a given input state s_t and an action a_t to the next state s_{t+1}. The transition probability is 1 for the states in the given range of the state space above, but 0 for the states out of it.

Reward R: The immediate reward that the agent receives at any time step t is a function of the current states and the control action taken by the agent, given by $r_t(s_t, a_t)$. We set up the reward function as illustrated below to induce the agents to realize the corresponding optimization objectives:

$$r_t = \sum_{i=1}^{k} (f_i(s_{t+1}) - pc_i) - \sum_{i=1}^{k} (f_i(s_t) - pc_i) \tag{4}$$

where pc_i denotes the expected granule performances of spray drier product output, and the $f_i(s_t)$ represents the prediction output (moisture content, 20 eyes, 40 eyes, 100 eyes) of the prediction model.

Discount rate γ: The discount rate γ for updating the loss function, when $\gamma = 0$, the agent only considers the immediate reward to take action. Conversely, when $\gamma = 1$, the agent will take action by considering all future rewards. We set it as 0.9 here.

The setting parameters of DQN after the experiment adjustment illustrate as follows. Here the number of time steps N set as 5000 for each episode, the replay memory size D is 2000, the learning rate is 0.01, and etc. In particular, the step F for updating DQN here denotes that the Q-networks would be updated at every 5 steps after 100 steps.

Using the preceding notations and definitions, the problem of production parameter optimization can be characterized formally as follows: through interactions between the agent and the environment, the agent is anticipated to discover the control strategies that maximize the cumulative rewards. Actual production can be guided by optimal production parameter conditions that meet quality criteria.

4 Experiment and Discussion

In this section, the experiment settings are explained and the simulations are performed by training the prediction model and the decision-making model. Experiments are conducted to examine the effectiveness of the proposed framework.

4.1 Ceramic Process Parameter Definition

Table 1. The value range in continuous process parameter

Process parameter	Type	Lower bound	Upper bound
Granule moisture (%)	Input	6.0	6.7
Granule unit weight	Input	0.892	0.935
Thickness of green bodies(mm)	Input	9.05	9.37
Moisture of dried green	Input	0.59	0.79
Temperature of kiln (°C)	In-process	Several temperatures of firing curve	
Rupture modulus (label 1)	Output	17.65	24.43
Water absorption (label 2)	Output	16.32	20.93
Biscuit size (mm) (label 3)	Output	607.53	609.14
Biscuit thickness (mm) (label 4)	Output	8.97	9.37

The background data in ceramic tile production utilized in this study to completed two sets of experiments. The data of the first set are: continuous process production parameters (Spray drier, Press, Kiln) include several parameters which before kiln as input variables, and process response parameters (e.g., quality characteristics of ceramic tile) as the output variables. The data set consists of 348 input-output pairs. Full details of the parameters are described in Table 1.

The data of the second set are: single session production parameters. The single session parameters collected from spray drier, including operating conditions and output granule performance record within a detection cycle. A few features of the proposed “Input”, “In-process”, and “Output” variables of spray drying are summarized in Table 2, where the 'In-process' variable is generated through internal treatments of spray drying. The data set consists of 203 input-output pairs. However, the process of ceramic tile production is mainly impacted by the complexity of the interdependent and correlated process variables, it is felt that a full theoretical understanding of spray drying treatments like all other complex processes would be helpful for 'production line' to achieve intelligent decision.

Table 2. Constraints and adjustment step sizes of spray drier production parameters.

Process parameter	Type	Lower bound	Upper bound	Step size(u)
Burning temperature (°C)	In-process	1001	1044	2
Inlet air temperature (°C)	In-process	640	659	1
Exhausted air temperature (°C)	In-process	97	125	2
Tower temperature (°C)	In-process	428	460	2
Slip feeding pressure (Mpa)	Input	30	33.2	–
Slip specific gravity	Input	1.68	1.707	–
Moisture content (%) (label 1)	Output	5.2	6.4	–
20 eyes(g) (label 2)	Output	0.15	0.54	–
40 eyes(g) (label 3)	Output	48.2	56.37	–
100 eyes(g) (label 4)	Output	0.41	2.16	–

4.2 Prediction Model Building Based on Various Parameters

According to the above two set of parameters, we are going to establish prediction model and give the prediction results to verify. In order to verify the prediction effect and combination with practical applications, we classified the output parameters. Generally, a standard range would be imposed on every output production quality feature. The median values of the upper and lower ranges of some feature parameters are better, and other feature parameters should not be lower than or exceed a certain limit value are better. It is unacceptable if the feature parameters are beyond the standard range, so the "In-process" variables must be controlled when the parameters are close to the boundary of the standard range. We divided the output parameters into two categories based on the experts' experience and production conditions, one representing the range (0) within which the "In-process" variables should be controlled, and the other representing the safety range (1) within which the operating conditions could be maintained. The classified details are described in Fig. 5 as follows:

$$\begin{cases} 1, & Q_{\min} + \lambda(Q_{\max} - Q_{\min}) \le Q \le Q_{\max} - \lambda(Q_{\max} - Q_{\min}) \\ 0, & Q \le Q_{\min} + \lambda(Q_{\max} - Q_{\min}) or Q_{\max} - \lambda(Q_{\max} - Q_{\min}) \le Q \end{cases} \tag{5}$$

$$\begin{cases} 1, & Q_{\max} - \delta(Q_{\max} - Q_{\min}) \le Q \le Q_{\max} \\ 0, & Q_{\min} \le Q \le Q_{\max} - \delta(Q_{\max} - Q_{\min}) \end{cases} \tag{6}$$

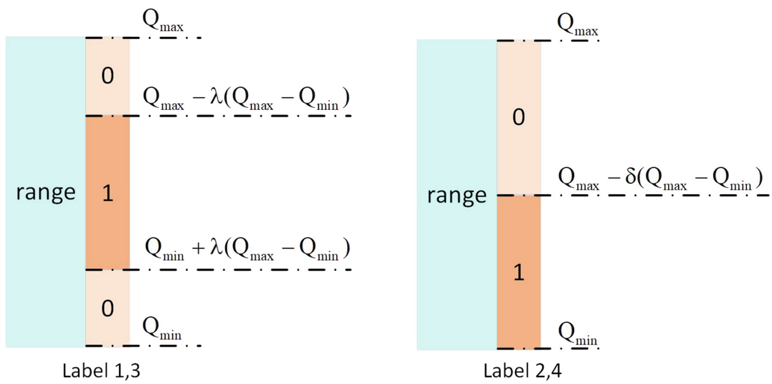

Fig. 5. Classification criteria for the parameters involved.

Where Q is the actual quality characteristic. The $Q_{\min}$ is the lower bound value and $Q_{\max}$ is the upper bound value. The threshold λ(0.25) and $\delta(0.5)$ is set up by the experts.

Prediction models are built according to the background data introduced in the subsection above. Next, we will complete the experiment of prediction models:

Experiment I: The first is a multi-session parameters model for optimizing the experimentation and process controlling.

Experiment II: The second is a spray drying process model for revealing the relationships between the input and output variables.

Multi-Session Parameters and Spray Drying Process Modeling and Prediction. For Experiment I, we trained the prediction models to predict the quality characteristics of ceramic tile. And the prediction result is obtained according to formula (7). The prediction performance of models displayed in Table 3. It is observed that the experimental results meet the expected requirements, and the prediction model is meaningful for practical engineering use. and the random forest prediction model has better prediction performance.

The overall classification accuracy, can be expressed as

$$accuracy\_score = \frac{TP + TN}{TP + FN + FP + TN} \tag{7}$$

where TP, FP, TN, and FN denote the classification results determined as true positive, false positive, true negative, and false negative, respectively.

Spray Drying Process Modeling and Prediction. for experiment II, We trained the prediction models to predict four objective granule performances of the spray drier output product. And the prediction result is obtained according to formula (7). The prediction performance was displayed in Table 4. It is observed that the experimental results meet the expected requirements, and could be used in the environment module for train the proposed decision framework. Random forest also has better prediction performance in this group of experiments. thus, we use the random forest to construct the environment part.