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Artificial intelligence in optical lens design

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Abstract

Traditional optical design entails arduous, iterative stages that significantly rely on the intuition and experience of lens designers. Starting-point design selection has always been the major hurdle for most optical design problem, and different designers might produce different final lens designs even if using the same initial specification. Lens designers typically choose designs from existing lens databases, analyse relevant lens structures, or explore patent literature and technical publications. With increased processing capability, producing automated lens designs using Artificial Intelligence (AI) approaches is becoming a viable alternative. Therefore, it is noteworthy that a comprehensive review addressing the latest advancements in using AI for starting-point design is still lacking. Herein, we highlight the gap at the confluence of applied AI and optical lens design, by presenting a comprehensive review of the current literature with an emphasis on using various AI approaches to generate starting-point designs for refractive optical systems, discuss the limitations, and suggest a potential alternate approach for further research.

Keywords Artificial intelligence · Optical lens design · Expert system · Deep learning · Reinforcement learning

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1 Introduction

Optical lens design is the starting point when developing an optical imaging system. It is the process of selecting and optimising a set of optical surfaces to meet desired constraints and performance criteria. Lens designers are required to manually predefine parameters of lens design based on their intuition and experience. Depending on the type of optical system being designed, parameters may include the arrangement of optical elements such as the aperture stop, and the definition of system characteristics such as the effective focal length, numerical aperture (NA) and field angle eventually leading to the definition of the Lagrange invariant. Figure 1 illustrates a generalised optical system which forms an image of an object at infinity, with its imaging characteristics defined by those parameters mentioned above. These form the basis of a starting-point design (SPD) that are further refined during optimisation, which involves an iterative procedure usually applied to minimise optical aberrations of a design while adhering to physical constraints.

Typically, lens designers employ optical design software with built-in optimisation algorithms which automatically varies the pre-determined optimisation variables of a SPD. There are also many prior works on the development of strategies and algorithms for lens design optimisation (Altameem et al. 2015; Carneiro de Albuquerque et al. 2016; Gagné et al. 2008; Menke 2018; Sheng et al. 2022; Sun et al. 2010). However, the multi-objective merit function landscape contains many local minima especially when the problem is intricate (Bociort 2010). Thus, the optimisation process remains heavily reliant on the chosen SPD.

Within the field of lens design, artificial intelligence (AI) approaches have been incorporated into the design process to enable automated suggestion of good SPDs, aiding lens designers in subsequent design optimisation. Expert systems were the earliest AI systems developed to automatically propose suitable SPDs (Chang 1986; Dilworth 1987; Livshits and Vasilev 2011; Weng et al. 1991). Due to the significant advances in computational resources, this is followed by the use of deep learning techniques which allow machine to propose SPDs based on the given reference designs and promising results from several studies point to the possibility of using these approaches for lens design generation (Côté et al. 2021; Tien et al. 2022). In addition, metaheuristic approaches have also been used or

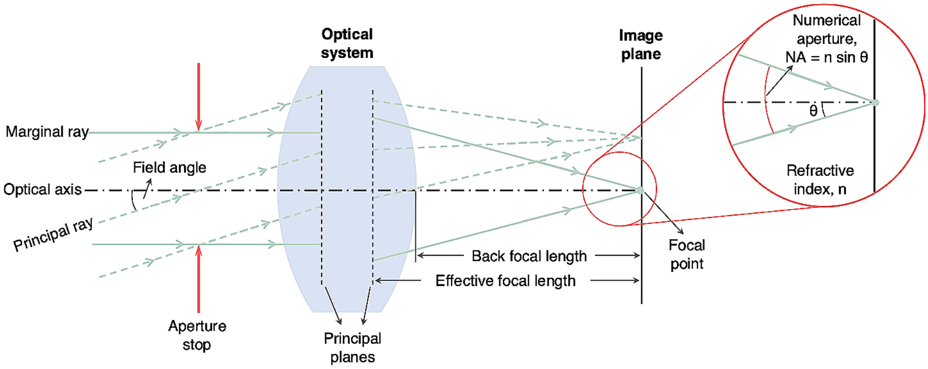

Fig. 1 Schematic sketch of a generalised optical system forming an image of the object at infinity to illustrate the critical parameters when designing optical systems

combined with neural network training in lens design (Antonov et al. 2023; Kononova et al. 2021; Qian et al. 2023).

In this Review, we examine literature pertaining to the use of AI approaches in the field of optical design, focusing on the generation of SPD for refractive lens systems. This review will discuss the application of expert systems, machine learning and deep learning approaches in the context of refractive lens design generation. Optimisation of SPDs generated by AI networks is considered to be outside of the scope of this review. Although metaheuristics approaches are broadly categorised as AI, these have been extensively reviewed before (Höschel and Lakshminarayanan 2019) and thus will not be covered in this current review.

The structure of this article is as follows. We first discuss the typical workflow employed by lens designers when designing optical systems. Subsequently, we highlight the primary challenge during the design process that has engendered a heightened interest with the exploration of AI approaches in generating good SPDs. Next, the AI approaches within the scope of the review are briefly introduced. Then, we provide a comprehensive review of the works specific to the development of expert systems and the application of deep learning approaches for SPD proposal and generation. We conclude by pinpointing the limitations of current approaches and contemplating the feasibility of alternative AI approach for SPD generation.

2 Typical lens design process

Lens design typically involves several steps to estimate and optimise parameters with specified tolerances for manufacturing. The design process relies on the combined expertise of a lens designer and computer-based tools (Juergens 1980). Figure 2 depicts the typical workflow for a lens designer in designing a lens system. To start, the lens designer selects a suitable SPD based on the required specification. Subsequently, the designer performs an initial evaluation of the compliance of the selected design to the performance requirements. If the evaluated performance is unacceptable, optimisation is required to improve the system performance.

Prior to optimisation, the lens designer must specify the merit function (MF), also known as the cost function or error function. The MF is a single number that represents the quality of an optical system (Bentley and Olson 2012) and is a function of optical system parameters such as radii of curvature of lenses, lens thicknesses, geometrical position of elements and refractive indices. It encapsulates all aspects of the required lens performance, including ray-based performance metrics like spot size and wavefront error, as well as parameters such as focal length, magnification, and size. Constraints like minimum or maximum lens thicknesses may also be used to ensure manufacturability of the lens system elements. Additionally, the MF can be tailored to evaluate properties such as the as-built performance of the optical system. With the defined MF, the lens designer uses built-in numerical optimisation in the lens design software to further improve the system performance while meeting the constraints.

After performing optimisation, the designer determines whether the optimised design meets the requirements. If it remains unacceptable, the lens designer repeats the preceding steps until the required specifications are met, which might also involve selecting a different

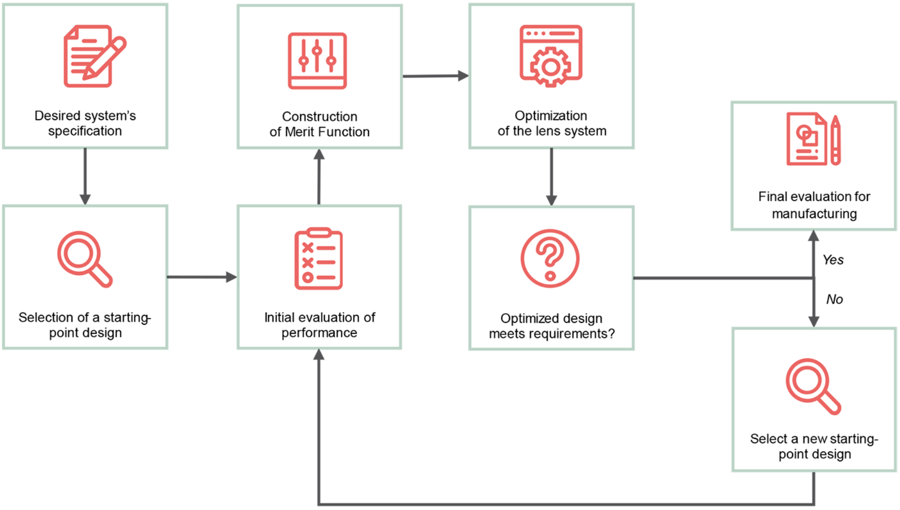

Fig. 2 Typical workflow for optical lens design, beginning with selection of starting-point design based on the given specifications, followed by initial evaluation and construction of merit function for further design optimisation. Final evaluation for manufacturing is performed only when the optimised design meets the requirement

SPD. Once the optimised design meets the requirements, a final evaluation including tolerancing, stray light and environmental analysis are conducted to ensure manufacturability and image quality.

3 Complex search space in optical design

As outlined above, the MF encompasses all necessary quantities for an optical design task. This leads to a highly non-linear multi-objective MF and a complex search space for optical system design (Sturlesi and O'Shea 1991). Weighting individual components of the MF is essential to attain desired overall performance, yet this often introduces conflicting objectives, such as optimizing image quality versus minimizing system volume.

Moreover, due to the non-linearity of the MF in optical design, numerous local minima exist, even in simple systems. Van Turnhout and Bociort (Turnhout and Bociort 2009) identified five local minima in a two-parameter system without constraints, while over 500 local minima were observed in a triplet system with six variables (Kononova et al. 2021). Hence, the search space in optical design features a plethora of local minima, steep gradients, and regions where the MF computation is infeasible, posing challenges to the convergence of local and global optimization algorithms.

4 Selection of SPD: "Well begun is half done."

With the aforementioned challenge, having a good SPD can aid in achieving a desired design quickly. In fact, lens designers play a significant role in the selection of SPD (Livshits and Vasilyev 2013). Depending on individual designers, the strategies used for selecting or creating SPD differ. The simplest approach is to select a starting-point arrangement from an existing database and optimize the design to meet the required specifications. In the absence of such database, designers may study the structures of available lenses and create a comparable SPD. Alternatively, designers can search patent literature and technical documents for solutions matching the desired specifications. When none of these approaches is feasible, designers create an SPD from scratch based on their knowledge of past lens designs or first-order principles. Despite having numerous options, it remains a challenge to determine the most effective approach for finding an optimal SPD (Bociort and van Grol 2012).

5 Artificial intelligence (AI)

Over the last few decades, lens designers have been continuously exploring ways to search or select appropriate SPDs for diverse applications. In this Review, we focus on the Artificial Intelligence (AI) methods which enable machines to automatically propose suitable SPDs with or without domain-specific knowledge expertise. We broadly categorised the various AI methods used in the literature into three subsets, namely Expert Systems, Machine Learning and Deep Learning (Fig. 3).

5.1 Expert system

Expert systems represent a pivotal milestone in AI history, being the earliest widely adopted and commercialized AI software. These systems employ if-else rules and domain-specific knowledge to solve complex problems traditionally requiring human expertise. An expert system typically comprises three core components: the Knowledge Base, Inference Engine, and User Interface (as depicted in Fig. 4). A Knowledge Engineer captures and organizes human expert knowledge into the Knowledge Base. When a user submits a query, the Inference Engine retrieves relevant knowledge, interprets it, and generates a solution. Forward Chaining and Backward Chaining are the two ways for acquiring knowledge from the Knowledge Base. Forward Chaining anticipates future outcomes by analysing facts and rules, suitable for tasks like decision-making. Conversely, Backward Chaining identifies causes or explanations for past events. These methods enable expert systems to efficiently solve problems and offer insights into decision-making processes.

5.2 Machine learning

Machine learning enables a machine to learn from historical data and previous experiences to identify patterns and make decisions without explicit programming for each type of problem. Supervised learning, unsupervised learning and reinforcement learning are the three primary categories into which machine learning can be further subdivided. As illustrated in Fig. 5a, supervised learning trains a machine using labelled datasets for making predictions

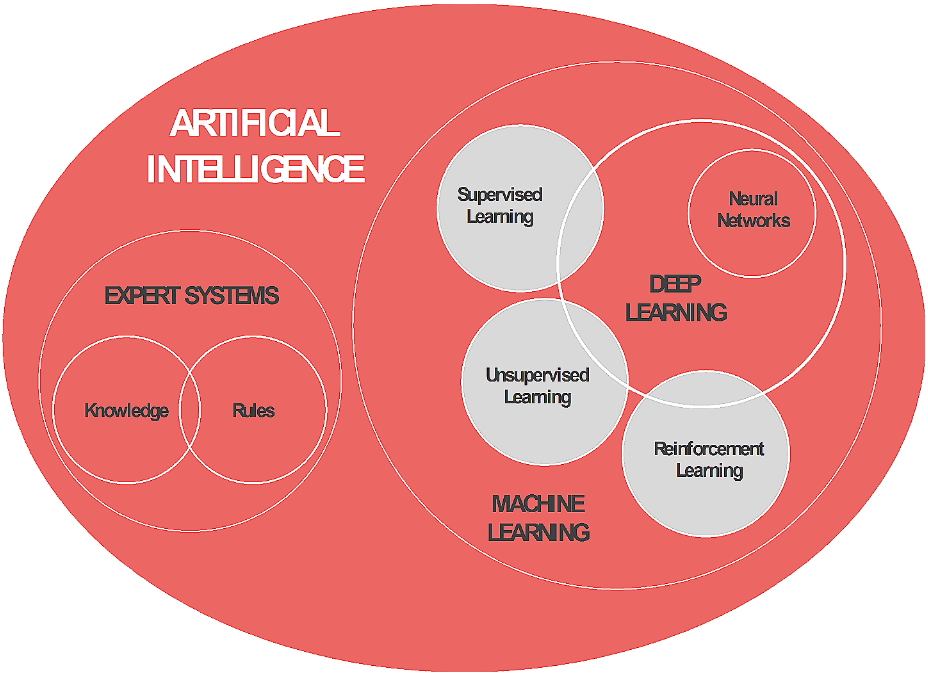

Fig. 3 Venn diagram showing Artificial Intelligence (AI) encompasses the subsets of Expert Systems, Machine Learning and Deep Learning, in which their methods can be applied to tasks that imitate human decision-making abilities

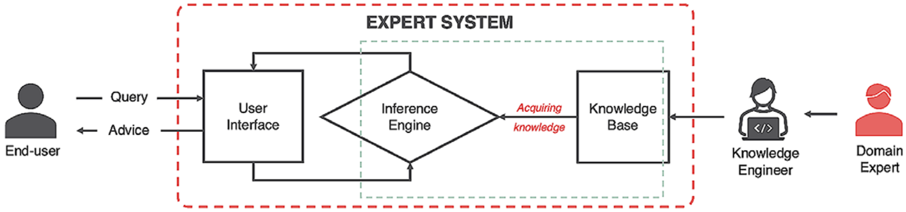

Fig. 4 Architecture of an Expert System shows the Knowledge Engineer classifies and structures the knowledge of a human expert to construct the Knowledge Base. Inference Engine uses forward chaining to deduce an outcome from the known facts and backward chaining to prove the known facts. User interface is developed for non-experts to interact with the system

by finding a function matching inputs to outputs. Unlike supervised learning (Fig. 5b), unsupervised learning makes use of unlabelled and unstructured data. The model is trained by searching for patterns or trends in data using clustering or association. Reinforcement learning (RL) is a different type of machine learning where an agent learns to make decisions by interacting with an environment. Through trial and error, the agent receives feedback in the form of rewards or penalties, adjusting its actions to maximize cumulative rewards.

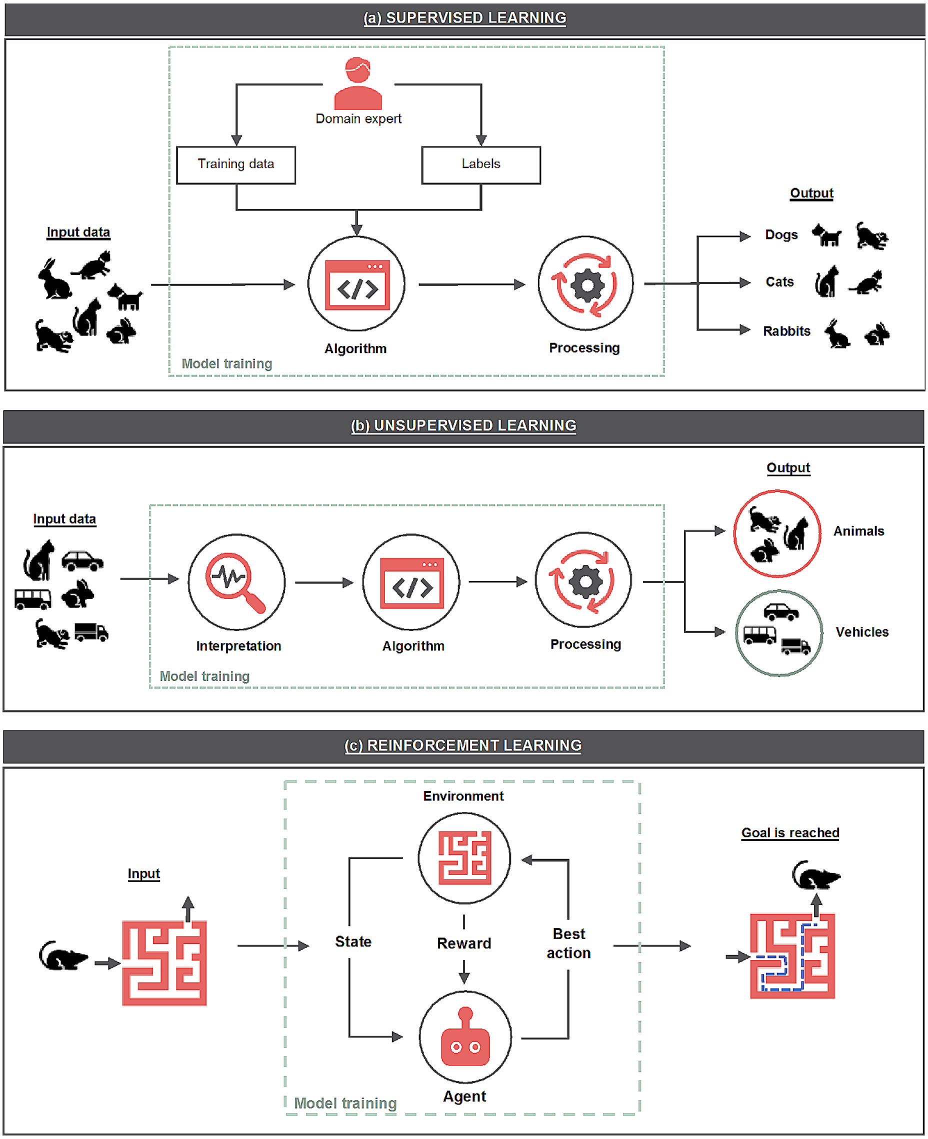

Fig. 5 (**a**) Supervised learning involves training a machine on labelled datasets to make intelligent predictions. A model is trained using a dataset consisting of images which are labelled by domain expert, and it acquires the ability to autonomously recognise and classify the images into their respective categories. (**b**) Unsupervised learning mitigates the need for manual data labelling and the model is trained by searching for similarities, differences, patterns, and structure within the unlabelled dataset using clustering or association. (**c**) Reinforcement learning (RL) distinguishes itself from supervised and unsupervised approaches by using rewards and punishments as feedback mechanisms to learn task-specific behaviours. As illustrated, the agent (mouse) learns to discover the optimal path out of the maze by exploring the maze (environment) and receiving positive or negative rewards for its actions (moving up, down, forward, or backward) in the maze

5.3 Deep learning

Deep learning, a subset of machine learning that relies on artificial neural networks inspired by the human brain's neural architecture. Deep learning involves training deep neural networks with multiple layers to extract features from input data and make predictions (Fig. 6a). At its core lies the artificial neuron (McCulloch and Pitts 1943), the basic computational unit that processes and transmits information. Modelled after biological neurons, artificial neurons receive input signals, apply weights to them, and pass the weighted sum through an activation function to produce an output (Fig. 6b). These neurons are organized into layers, forming neural networks capable of learning complex patterns and relationships in data. Unlike traditional machine learning, deep learning demands substantial computational resources and vast datasets.

6 Application OF AI to starting point design

In this section, we review the works specifically for refractive lens design generation that used the aforementioned AI approaches. Table 1 provides a summary of these works.

6.1 Development of expert system for SPD proposal

Many prior studies have focused on developing expert systems to facilitate the generation or selection of a suitable SPD. To develop an expert system which can automatically propose SPDs, it generally requires the knowledge and experience of the lens designer as well as lens design formulae to be transcribed into rules and algorithms (Fig. 7). In the case of lens design, inference engines use backward chaining method to infer SPD that meets the specified requirement.

The earliest expert system for lens design was developed by Chang (Chang 1986) which has an interactive user-interface, a global database and a knowledge base built from optical textbooks and papers. The user responds to true-or-false questions posted by the system, and the system uses the backward chaining method (Russell 2010) to deduce the system type and proposes the appropriate lens design patent that meets the user requirements. In 1987,

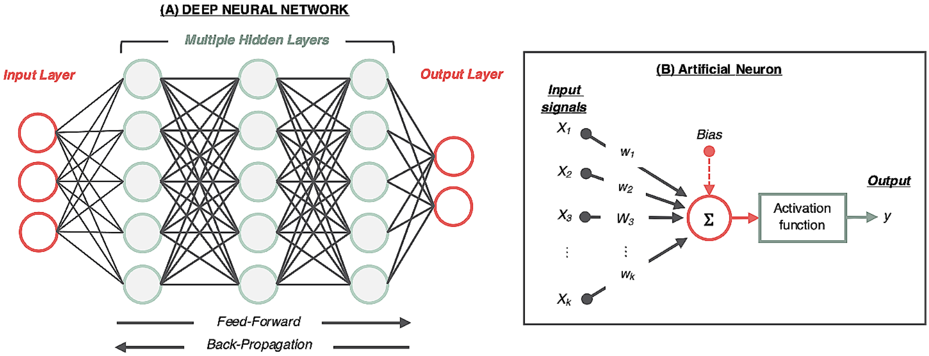

Fig. 6 (**a**) A typical Deep Neural Network is formed by connecting artificial neurons akin to the neurons in the human brain. (**b**) Each artificial neuron has input nodes, an activation function and output nodes

Table 1 A summary of previous works pertaining to the application of AI approaches in optical lens design, specifically the generation and/or suggestion of starting-point designs for refractive systems

Year	Authors	Title	Method		Is database required?	Main objective	Targeted lens designs
			Expert system	Deep learning			
1985	(Chang 1986)	Analytical Lens Design By Microcomputer With Artificial Intelligence	✓		✓	To suggest appropriate lens patent design for reference	Wollaston meniscus, achromatic meniscus, Rapid Rectilinear, Wide-angle Anastigmat, Zeiss Protar, Petzval lens, Zeiss convert Protar, Dagor, Lister, Tessar, Cooke triplet, Celor
1987	(Dilworth 1987)	Applications Of Artificial Intelligence To Computer-Aided Lens Design	✓		✓	To provide engineering decisions and best-match designs	Infrared systems
1990	(Chang and Chen 1990)	Optical design by artificial intelligence techniques	✓			To solve first-order optical design problems using equations	Telescope
1990	(Weller 1990a)	Neural Network Optimization, Components, and Design Selection		✓	✓	To replace expert system with neural net classifier, and make a database selection	Double Gauss, Petzval
1991	(Weng et al. 1991)	Attempt to develop a zoom-lens- design expert system	✓		✓	To automate the optical lens design process for zoom lens, with selection of starting point from database based on input requirements	Zoom lens
1992	(Nouri 1992)	Knowledge-based optical system design	✓			To generate starting-points for centred dioptrical, on-axis and low aperture optical systems	Monochromatic and polychromatic optical systems (singlet, doublet, triplet, reversed singlet, reversed doublet, reversed triplets, telescopes)
1993	(Johnston et al. 1993)	Combination of global-optimization and expert-systems techniques in optical design	✓		✓	To generate starting-point for monochromatic lens designs	Monochromatic quartet
1993	(Chen et al. 1993)	Small expert system used in lens design	✓		✓	To select initial configuration of triplets from pre-defined database	Triplet lens

Table 1 (continued)

Year	Authors	Title	Method		Is database required?	Main objective	Targeted lens designs
			Expert system	Deep learning			
1993	(Anitropova 1993)	Simple method for computer-aided lens design with the elements of artificial intelligence	✓			To select starting-point designs for a centred lens with fixed characteristics and infinite object	Optical elements formed by concentric, aplanatic, planar, and near-image surfaces.
1993	(Hu et al. 1993)	Optical lens design by neural network		✓	✓	Using neural network to classify lens designs based on shape factor and power of lens	Not applicable
2005	(Cheng et al. 2005)	Expert system for generating initial layouts of zoom systems with multiple moving lens groups	✓		✓	To automatically generate initial design layouts for zoom systems with multiple moving lens groups	Zoom systems with moving lens groups
2009	(Livshits and Vasiliev 2009)	Information technologies in CAD system for lens design	✓			To automatically synthesize new lens starting points	Telescopes, photographic lens, micro-objective lens and relay lens
2012	(Mouromtsev et al. 2012)	Knowledge based engineering system for structural optical design	✓			To automatically synthesize new lens starting points according to the functional purpose of each optical surface	Photographic objectives
2018	(Côté et al. 2018)	Toward Training a Deep Neural Network to Optimize Lens Designs		✓	✓	To generate optimized two- lens designs	A system of two lens elements
2019	(Côté et al. 2019a)	Extrapolating from lens design databases using deep learning		✓	✓	To infer optimal two-lens telescopic objectives for any given set of specifications	Cemented and air-spaced doublets
2019	(Côté et al. 2019b)	Introducing a dynamic deep neural network to infer lens design starting points		✓	✓	To infer lens variables in a sequential manner	7 different lens design structures selected from Zebase 6 Optical Design Collection
2021	(Côté et al. 2021)	Deep learning-enabled framework for automatic lens design starting point generation		✓	✓	To automatically generate starting-point designs based on desired effective focal length, f-number and half field-of-view	80 different lens design structures extrapolated from Zebase 6 Optical Design Collection

Table 1 (continued)

Year	Authors	Title	Method		Is database required?	Main objective	Targeted lens designs
			Expert system	Deep learning			
2022	(Côté et al. 2022)	Inferring the solution space of microscope objective lenses using deep learning		✓	✓	To generate a variety of microscope objective lenses that are similar in structure to the reference designs, but with varied element sequences	Microscope objective lens
2022	(Tien et al. 2022)	Design of a Miniaturized Wide-Angle Fisheye Lens Based on Deep Learning and Optimization Techniques		✓	✓	To find the best combination of various lens materials for five-element wide-angle fisheye lens	Miniaturized wide-angle fisheye lens
2023	(Nie et al. 2023)	Freeform optical system design with differentiable three-dimensional ray tracing and unsupervised learning		✓	✓	Using neural network with unsupervised strategy to provide starting-point designs for reflective/refractive and aspheric/freeform optical systems	Aspheric eyepiece

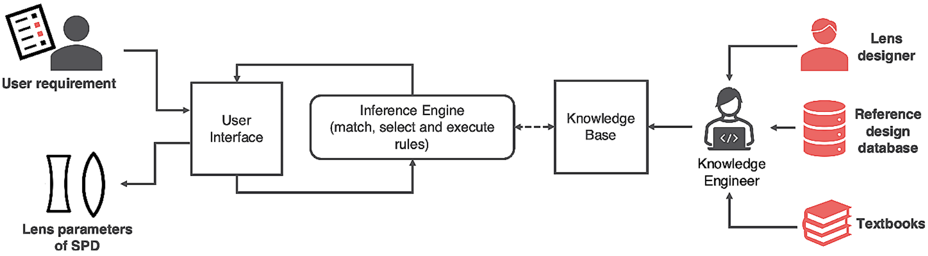

Fig. 7 A typical framework of an expert system for SPD proposal based on user requirement via a user interface, involving the transcription of expert knowledge, reference designs and theoretical concepts from textbooks into algorithm

Dilworth developed an expert system which was incorporated with the knowledge of an experienced lens designer and used tree-structured logic to facilitate engineering decision-making (Dilworth 1987). The system suggested ten realisations for an infrared (IR) design problem, which were then evaluated by human experts. It was observed that the failure of the system can be attributed to the absence of field lens in all designs. However, the author highlighted that field lenses are not utilised in IR design and the system effectively circumvented the error that human experts may have made. Chang and Chen further demonstrated the efficacy of their expert system by transforming the formulae and practical experience of designing telescope into equations and production rules, and then integrating them into the system (Chang and Chen 1990). However, the paper provides insufficient information as to the process by which the formulae and experience were translated into rules. The authors evaluated the system by designing a telescope with the given specifications and subsequently concluded that expert systems could be powerful tools for solving first order optics problems.

In later years, lens designers attempted to combine expert system and optimisation algorithms such that the lens design process is seen as fully automated. This concept is first demonstrated by Weng et al. (1991). Based on the experience and knowledge of researchers in their institute, the MEX-1 system was developed and integrated with optical design software to enable automated zoom lens design. The system also had a database consisted of more than 2000 optical lenses, of which, 500 were zoom lens. In addition to optical lenses, the database also contained approximately 1000 different optical materials. The MEX-1 system first selects a SPD from the database based on the input requirements and the optimisation of the selected design and evaluations of image quality are performed separately with an optical design software.

Johnston et al. showed that the combination of expert system technique and optimisation is capable of locating SPD (Johnston et al. 1993). They created a database of nine sets of similar monochromatic lens designs which were not well-optimised. Using this database, the expert system suggested ten SPD for a monochromatic quartet and the designs underwent quick optimisation. The authors suggested that the expert system can be beneficial in finding SPD that leads to global solution after optimisation. Furthermore, the utilisation of a simplex downhill optimisation technique enables the exploration of additional good designs achieved from the existing database collection, which further allows expert system to construct new initial designs.

(Chen et al. 1993) also developed an expert system that assists users in selecting appropriate starting configurations of triplets from a small database for further optimisation using methods similar to those utilized in the earlier work by (Chang and Chen 1990). The primary distinction in this work is the inclusion of a certainty factor that varies from 0 to 1. A certainty factor of 0 indicates that the evidence pertaining to the specified design problem is unclear, while a value of 1 signifies that the evidence is certain. The algorithm conducts a search for evidence that match the defined rules and computes the factor which is then used for uncertain inference.

Nouri and Erard developed a new approach which generates SPD of centred dioptrical optical systems with low NA, taking into account of the system physical constraints and optical quality, without the need to create any lens database (Nouri 1992). The approach is implemented by transferring the knowledge of optical design and optical properties to the computer through logic programming. The inference engine is equipped with backtracking that uses a brute force approach to find all possible solutions. The authors showed that the proposed approach can generate good quality SPD for triplet and doublet lenses which demonstrated rapid convergence of merit function optimisation (Nouri and Erard 1993).

Anitropova used a different approach to develop an expert system for selection of SPD (Anitropova 1993). Instead of a pre-defined lens design database, the author used a heuristic approach with approximately 600 rules to generate variants of optical scheme which is expressed in the form of a structural formula. The process by which the rules were acquired and developed remains ambiguous. The proposed approach requires various input parameters including f-number, field angle, and focal length, to determine the system type, and the algorithm selects the SPD appropriately. However, the optical scheme is only limited to optical elements with concentric, aplanatic, planar, and near-image surfaces.

Expert systems were further developed for more sophisticated optical systems. Cheng et al. developed a system that automatically generates SPD for complex zoom systems with multiple moving lens groups (Cheng et al. 2005). Based on the input specifications of smallest effective focal length, zoom ratio, maximum field-of-view, and other constraints, the system computes the optimised parameters pertaining to an unaberrated optical system and constrains the f-number of each lens group. The lens groups are then automatically selected from a database which was established based on approximately 2,000 zoom lens patents. The system evaluates all possible combinations and outputs the satisfactory ones. It was noted that the system could generate designs free of ray failures, but usability of these designs as SPD was not fully evaluated.

Recently, Livshits et al. developed an expert system called STRUCT to automatically synthesise lens designs (Livshits and Vasilev 2011; Livshits and Vasiliev 2009). The authors formalised the structural synthesis process using a heuristic algorithm and the expertise of a lens designer. The resulting system is made up of four distinct algorithms, each for a distinct optical system (telescope, photographic, micro-objective, and relay). The selection of the SPD is guided by technical specifications provided by users. The authors also introduced an index by aggregating the complexity values of all technical specifications to indicate the complexity of the optical systems. Mouromtsev et al. then introduced ontological approach when developing an expert system in 2012 (Mouromtsev et al. 2012). The utilisation of ontology enabled structural analysis of optical systems and determination of the function of each optical element within the optical system, leading to the formalisation of the design process. The expert system effectively proposed a list of structural designs for a photographic objective based on the specified specifications.

6.2 Application of machine learning and deep learning for SPD generation

Given the successful application of deep learning in various domains (He and Deng 2017; Kim et al. 2021; Kuutti et al. 2019; Mahapatra et al. 2019; OpenAI 2023; Shaukat et al. 2023; Silver et al. 2016), there is an increasing interest to apply machine learning and deep learning techniques to aid lens designers in generating appropriate SPDs. A typical framework of applying deep learning approaches to generate SPD is illustrated in Fig. 8. The model development involves the use of neural network, reference designs of desired specification and ray tracing for evaluating the output designs. The deep learning model undergoes training and gradually improves the prediction as it minimises the loss between the output design and the reference design.

The concept of applying neural network for optical lens design selection was first demonstrated by (Weller 1990b). The aim of this work was to show that expert systems can be replaced by neural networks without the explicit inclusion of optical design rules. By training a three-layer neural network with actual lens designs, Weller showed the trained network can select SPD from a database based on the user requirements. The result also suggested that the selected types of lenses which were used for training need to be well-defined to avoid confusing the neural network during training (Weller 1990a). In 1993, Hu et al. developed a multi-layer back-propagation neural network model to classify lens designs based on the specified lens shape factor and lens power, and optimise optical aberration given target spot size (Hu et al. 1993). The authors successfully showed that the optical design rules can be translated into weights of a neural network system and that the trained network was able to perform classification and optimisation.

Extending their earlier work (Côté et al. 2018), which used a deep neural network (DNN) to generate optimised designs for two lens system, Côté et al. explored a hybrid approach (Côté et al. 2019a) by incorporating both supervised and unsupervised training. By minimising a loss function representative of root mean square (RMS) spot size, the DNN is trained to map the provided specifications to reference lens designs from the database. This is followed by unsupervised training in which the network infers the lens systems from randomly drawn sets of specifications, optimises the optical performance and enables generalisation across varied specifications. Their hybrid training approach successfully inferred designs

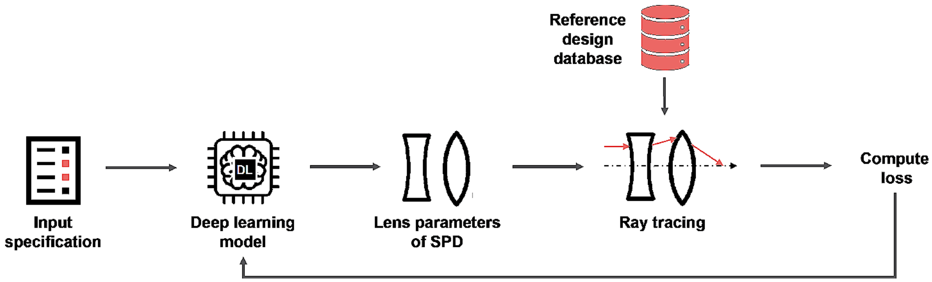

Fig. 8 Typical deep learning model development for generating SPD, involving the training of deep neural network with given reference design database

for cemented and air-spaced doublets with optical performance comparable to reference designs.

A more dynamic model based on a Recurrent Neural Network (RNN) (Marhon et al. 2013) architecture was later introduced to infer SPD by extrapolating from known databases (Côté et al. 2019b). The proposed model takes entrance pupil diameter and half field-of-view as input and sequentially infers the lens parameters such as curvatures, refractive indices, Abbe number and thicknesses. The model is also trained with the hybrid approach, using seven different lens design structures chosen from the Zebase 6 Optical Design Database (Corp. 2007). The authors compared the existing DNN model to the new dynamic model, and the experimental results showed that, although the RMS spot sizes achieved by both models are not significantly different, the proposed dynamic model generally produces designs closer to the reference lens design. Furthermore, the authors demonstrated the advantages of using transfer learning, allowing the model to generalise to new lens design structures and achieve better optical performance compared to training a model from scratch. The proposed dynamic model was limited to a few lens structures, making it unsuitable for real-world lens design problems. Côté et al. improved the model by allowing the aperture stop to be placed anywhere in the design, including vignetting factor as input specification, and deriving glass variables that closely approximate the behaviour of discrete glass materials in the Schott glass catalogue (Côté et al. 2021). The improved model was trained using a dataset consisting of 80 lens constructions that were extrapolated from 150 reference designs in the Zebase 6 Optical Design Database. The trained model can infer viable lens design structures such as Cooke Triplets and Double Gauss Lenses, with acceptable optical performance.

The model was further extended to microscope objective lens design. The authors adapted the concept of one-to-many mapping to generate variations of objective lens designs for a given set of specifications and lens sequence (Côté et al. 2022). 7,432 lens sequences were generated using 34 reference lens designs from the microscope objective dataset created by Zhang and Gross (Zhang and Gross 2019), which include all feasible combinations of five to ten glass elements and different stop positions. They demonstrated that the trained model can extrapolate across diverse specifications, lens sequences and structures, including Lister-type and Double-Gauss designs, to achieve good SPD for microscope objective lens.

Deep learning was also combined with optimisation step to design a miniaturized wide-angle fisheye lens by (Tien et al. 2022). The authors trained a DNN model on 106 different lens materials and the model can infer the best combinations of lens materials based on the variables (curvature, thickness, refractive index, and Abbe number) of the initial configuration. The authors conducted further optimisation of the output design using commercially available optical design software, and the results indicate that deep learning can potentially assist in designing wide-angle fisheye lenses.

In another recent study, Nie et al. developed a deep learning framework for generating aspheric eyepiece designs using unsupervised training technique (Nie et al. 2023). The authors compiled a collection of 2,625 eyepiece designs, each with distinct specifications. The framework employs a DNN architecture comprising 20 stacks, each containing nine layers with 64 neurons per layer. The network is trained using approximately 78% of the generated dataset and validated with the remaining data. With input parameters of entrance pupil diameter, FOV and the materials, the trained model predicts the surface positions and surface coefficients. The validation results showed that 96.5% of the generated designs achieved RMS spot size below 50 µm, with no ray loss and distortion below 5%. Nonetheless, 1.2% of the designs had overlapping of optical components.

7 Limitations

As detailed above, AI has been successfully applied in the field of lens design to aid lens designers in establishing suitable SPD with or without domain-specific knowledge expertise. In this section, the limitations of the prior works are identified and discussed.

7.1 High development and maintenance cost for inflexible systems

Expert systems enable lens designers to save time in selecting SPD for optical systems by only providing the required specifications. However, implementing such expert systems requires meticulous translation of optical design principles and the explicit definition of design rules into computer algorithms. Expert systems lack genuine intelligence since encoding intuitive insight of experienced lens designers into quantifiable system logic and reasoning poses a formidable challenge (Bell 1985). The effort and cost for system implementation and testing dramatically increase with system complexity as additional resources are required to break down the decision process and design strategies. Moreover, the use of expert systems for SPD selection can be limited by the outdated knowledge base over time and the emergence of unforeseen design problems.

7.2 Necessary establishment of databases

It is evident that most expert systems and deep learning approaches require establishing databases. The knowledge base in expert systems is similar to a database that comprises rules and designs of particular types of lenses, while deep learning necessitates the curation of the targeted lens type. It is noteworthy that majority of the works involve extrapolation or generation of lens designs to augment the training dataset since readily available lens designs are insufficient for deep model training. A recent investigation by Buquet et al. reveals the limitation of data-driven approach (Buquet et al. 2022). In this study, the authors trained both linear and non-linear models to predict RMS spot size from the given distortion function of wide-angle system designs. Upon comparing these trained models, they found that the training set and parameter dimensionality restrict prediction model reliability and performance. This highlights the fundamental challenge of using a reference database as a training set, especially when a lens type has limited configurations.

7.3 Limited diversity of designs and application-specific

Although recent works have successfully demonstrated that the use of deep learning in lens design eliminates the need for explicit programming of rules and domain knowledge, it is important to note that the effectiveness of training deep learning models depends highly on the diversity and quantity of the available training data. In other words, the output lens design is inherently constrained to the configurations of the optical systems that were used for training. As deep learning approaches entail the blind training of a black-box model without any pre-existing knowledge pertaining to optical design, retraining of deep models is required when applied to different system applications.

7.4 Challenges in performance evaluation

The growing use of AI in various fields has led to the need of having publicly available datasets to facilitate the reproducibility and comparability of AI approaches. However, within the field of lens design, a notable gap persists in the availability of publicly accessible benchmarks for SPDs, hindering the comparison of developed AI approaches. Presently, the performance of AI approaches is qualitatively evaluated either by comparing their output designs with those provided by human experts or by assessing the output designs based on factors such as design structures, modulation transfer function (MTF), and transverse ray aberration. Hence, the absence of standardised evaluation metrics across various AI approaches exacerbates this challenge. The performance evaluation of AI approaches is also confined to individual studies rather than being systematically compared across multiple studies.

8 Future of AI in optical design: "learning to design"

One significant limitation of expert-driven and deep learning approaches is the requirement for reference lens designs, which has not yet been overcome. The question remains if an approach for the generation of optical lens design can be developed without the need for an explicitly-defined reference database.

To date, reinforcement learning (RL) has not been fully explored for optical lens design. RL diverges from conventional data-driven methodologies by facilitating dynamic learning to ascertain the optimal decisions that yield the desired outcome. It has garnered significant attention across various research domains and has been successfully applied to fields such as gaming (Mnih et al. 2013; Vinyals et al. 2017), robotics (Beltran-Hernandez et al. 2020) and autonomous driving (Zhu et al. 2020).

However, within the realm of optical design, the application of RL methods has been limited to the optimisation of parameters in optical thin films (Jiang et al. 2021), freeform imaging systems (Yang et al. 2020) and basic lens systems (Fu et al. 2021; Fu et al. 2022). Specifically, Fu et al. demonstrated the use of RL in automatically optimising a two-symmetrical-lenses system (Fu et al. 2021) by changing lens curvatures to reduce spherical aberration. They successfully demonstrated the ability of the trained agent in choosing different curvatures as optimisation parameters for five pre-defined SPD using both Proximal Policy Optimization (PPO) (Schulman et al. 2017) and Advantage Actor Critic (A2C) (Mnih et al. 2016) algorithms. Moreover, the trained agent can change lens locations for focal length adjustment in a pre-defined varifocal system (Fu et al. 2022), and optimise the surfaces and distances for a given Cooke Triplet system to meet the desired specifications.

Beside lens parameters optimisation, RL can potentially be used to generate SPDs and offers several key benefits. From the envisioned framework shown in Fig. 9, one notable advantage is the absence of a requirement for a reference design database to train the RL agent. Instead, the agent independently explores the possible state-action pairs to achieve the objective of the design task. These state-action pairs or experiences, coupled with the

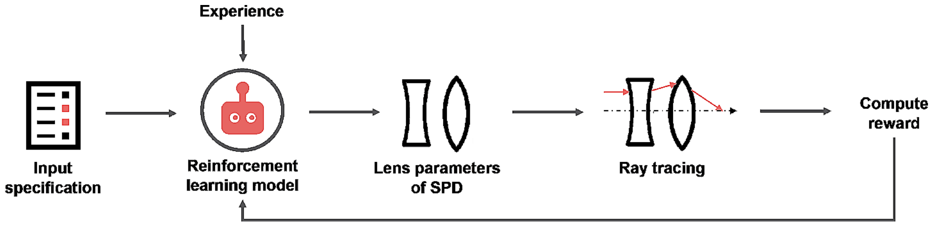

Fig. 9 Envisioned framework for reinforcement learning (RL) model development for SPD generation. For every output SPD, it is evaluated by finite ray tracing and reward is given to the agent according to the evaluation to form a set of experience. The RL model improves its decision as more experience is gained

reward signal, are used to train the deep model within the agent. This eliminates the need for a curated training dataset and enhances adaptability to a larger variety of design requirements. Additionally, RL techniques allow thorough exploration of the solution landscape which potentially yields SPD that differ from those manually chosen by human experts. This ability is valuable from the physics perspective, allowing us to investigate the effectiveness of current lens design principles in achieving feasible and stable optical systems. For instance, while aplanatic-normal surfaces can reduce and/or eliminate certain aberrations at those surfaces, they may not represent the optimal strategy when considering the entirety of a given optical system.

Up to this point, RL methods have primarily been applied in simple design problems where model training is relatively straightforward. When the intricacy of the design problem increases, so does the complexity of the RL model. In such cases, the agent requires a greater number of experiences, coupled with more extensive exploration to improve its decision-making capabilities. However, excessive exploration may potentially impact the model performance. Consequently, determining the optimal balance of experiences for acquiring the best policy becomes a challenge, and the choice of the appropriate exploration approach becomes a critical consideration in RL (Rehman and Tomar 2019). In the context of SPD generation, the ability of current RL techniques to manage highly complicated designs remain uncertain. A further challenge encountered in RL development pertains to reward engineering (Dewey 2014). The agent relies heavily on rewards and penalties for decision-making and execution, necessitating meticulous consideration when implementing a reward mechanism that effectively aligns with the objectives of complex tasks.

9 Conclusion

Optical lens design process includes the selection of suitable starting-point design (SPD), the evaluation of its adherence to performance requirements, and the subsequent optimization. The selection of SPD plays a pivotal role in attaining the desired design quickly. Consequently, lens designers continue to be interested in finding a viable solution for automatic selection or generation of SPD. This review reveals that there has been significant interest in applying AI techniques including expert systems and deep learning approaches, for generating SPD. However, reinforcement learning (RL) techniques remain unexplored in lens design generation and further investigation is necessary to ascertain its applicability. We posit that RL will play a collaborative and complementary role in the design process, and the prospect of possibly attaining optimal optical designs holds great promise for a tantalising and exciting future.

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Declarations

Competing interests The authors declare no competing interests.

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