Applications of Artificial Intelligence Techniques for Optimization of Structural Steel Connections

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APPLICATIONS OF ARTIFICIAL INTELLIGENCE TECHNIQUES FOR OPTIMIZATION OF STRUCTURAL STEEL CONNECTIONS

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Abstract: Steel connections in building projects are traditionally designed in Canada by the fabricator's engineer using connection design software or spreadsheets, often supplemented by hand calculations. Implicit in these processes is the desire to optimize the net fabrication and erection costs based on several parameters such as material, task and process repetition, machinery availability, fabrication and erection constraints, and available optimization tools. This study aims to explore the realm of structural optimization by employing evolutionary algorithms to automate and optimize the design of steel shear connections. Evolutionary algorithms are search algorithms used within artificial intelligence to determine an optimal solution from a population of possible solutions within user-defined optimization criteria. A design optimization tool built using parametric modelling and connection design software utilizing component-based finite element modelling is applied to a shear end plate connection. The results are tested and compared against an example end plate connection design from the Canadian Handbook of Steel Construction. The optimization results showcase the potential of using evolutionary algorithms for steel connection design, and the practicality of the optimization tool for use in a professional environment is presented.

1 INTRODUCTION

Applications of artificial intelligence (AI) techniques within the steel construction industry offer the potential for optimization of connections in ways not possible without utilizing advanced computational resources. In Canada, steel connections in building projects are typically designed with the aid of connection design software, spreadsheets, and design tables, while complex connections may involve numerical behavioural simulations using commercial finite element analysis software. Designing what may be thousands of connections in a typical project can be an extremely time-consuming process, especially when aspects of the design change throughout the lifecycle of the project. Unfortunately, changes are common and unavoidable in the construction industry and have left connection designers redoing or recalculating a large number of their designs, leading to a loss of efficiency and productivity (Greco 2018). Development of design tools that utilize AI-driven techniques can provide instant feedback to designers on how certain changes affect cost, constructability, and sustainability, while allowing for the efficient design of connections and better integration of the workflow across different disciplines (Ebrahim et al. 2020).

This study investigates the practicality of an optimization tool that utilizes evolutionary algorithms (EA) to optimize shear connections such as shear tabs, welded–bolted double- and single-angle connections, and all-bolted double- and single-angle connections, shown in Figure 1. To illustrate the main principles, a shear end-plate connection is explored using the demand-to-capacity ratio as the optimization criterion. The various aspects that contribute to the development of the optimization design tool, as well as the limitations of this tool, are explored in the following sections.

2 METHODOLOGY

2.1 Virtual Connection Test Matrix

The shear connections evaluated in this study were chosen based on an industry survey conducted by the Steel Centre at the University of Alberta (Oosterhof and Driver 2014). The survey was sent to local steel fabricators in Edmonton, Canada, where connection designers ranked common steel shear connections on a scale of one to five, with one corresponding to “rarely used” and five corresponding to “heavily used”. The results of the survey were averaged, and the top six connections were incorporated into the optimization design tool. In addition to six different connection types, the design tool consists of a beam-to-girder connection, beam-to-column-flange connection, as well as a beam-to-column-web connection, all shown in Figure 2. Within the tool, the user can opt to use codified limit states design provisions or component-based finite element modelling (CBFEM) to determine the capacity of the connection. The design of a shear end plate in a beam-to-column-web connection through the proposed optimization tool is illustrated in this paper. The results are then compared to end plate connection design example in the Handbook of Steel Construction (CISC 2017).

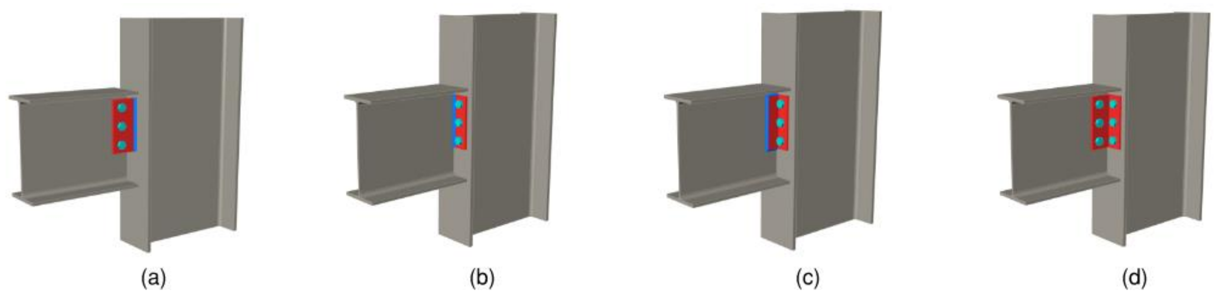


Figure 1: Simple shear connections: (a) Shear tab, (b) Shear end plate, (c) Welded–bolted angle connection, (d) Bolted angle connection

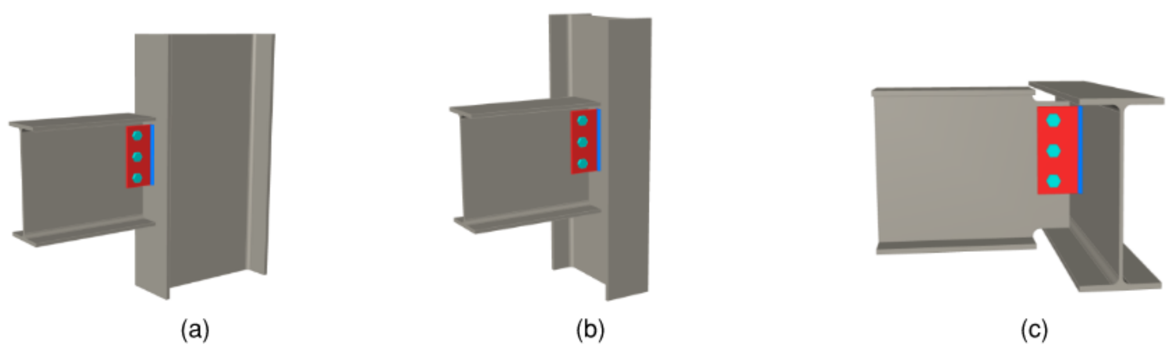


Figure 2: Selected connection configurations: (a) Beam-to-column-flange connection, (b) Beam-to-column-web connection, (c) Beam-to-girder connection

2.2 Proposed Connection Optimization Tool

In order to perform generative design, a parametric model is developed through Grasshopper, a visual scripting plugin for Rhino3D (Robert McNeel & Associates 2021) used for parametric design, where Rhino3D is a 3D computer graphics and computer-aided design application software. Parametric modelling is the creation of a digital model based on a series of pre-programmed rules. That is, instead of the model or elements being manually manipulated, they are generated automatically by internal logic arguments. Typically, parametric rules create relationships among different elements of the design. For example, a rule might be created to ensure that the pitch between rows of bolts remain a specified distance; if the number of bolt rows changes, the distance between adjacent bolt rows remains the same.

The user interface of the proposed optimization tool allows the designer to choose the connection type, beam and column size, steel grade, bolt diameter, number of copes, and bolt pitch. For each connection type, the parametric attributes outlined in Table 1 are then used to control the design for the respective connection. Aspects of the connections, such as edge distance, bolt spacing, bolt hole diameter, plate thickness, weld size, etc., are constrained through limitations prescribed by the Canadian steel design standard CSA S16 (CSA 2019).

Table 1: Modelling parameters for shear connections

Connection Type	Parameters
Shear end plate	Plate thickness, number of bolt rows, fillet weld size
Shear tab	Plate thickness, gauge distance, number of bolt rows, number of bolt columns, fillet weld size
Welded–bolted double angle Welded–bolted single angle	Angle designation, number of bolt rows, fillet weld diameter
Bolted double angle Bolted single angle	Angle designation, number of bolt rows

2.3 Evolutionary Algorithms (NSGA-II)

EA are optimization algorithms that search for optimal solutions by mimicking the biological mechanisms of mutation, recombination, and natural selection (Bagavathi and Saraniya 2019). In the presence of multiple objectives in a problem, which is often the case in connection design, a set of optimal solutions arises as opposed to one optimal solution. Because of this, applications of EA in structural engineering are often referred to as generative design, which is the act of generating thousands of design iterations with the intent of having an engineer choose one solution from a set of optimal solutions.

Over the last decade, numerous EA have been developed as technology rapidly advances and the field of AI becomes more prominent. For this study, a sorting-based multi-objective EA called nondominated sorting genetic algorithm II (NSGA-II) is used (Deb et al. 2002).

NSGA-II solves multi-objective optimization problems (MOPs) through Pareto dominance and a sorting procedure known as non-dominated sorting. A solution is considered to dominate another solution if all its fitness values, determined from the user-defined objective criteria, are lower than or equal to another solution's fitness values. For the proposed optimization tool, the fitness values are based on the demand-to-capacity ratios determined through the two analysis methods. An example of non-dominated sorting for a double objective problem is illustrated in Figure 3. During non-dominated sorting, solutions are compared against each other and are assigned ranks based on dominance. Lower ranks refer to better fitness values and are associated with solutions that have higher dominance. In MOPs, a solution is said to be a Pareto optimal solution if it is not dominated by any other solution of the MOP. There exists more than one Pareto optimal solution for an MOP due to the conflicting nature of objectives. The projection of Pareto optimal solution set in objective space is called the Pareto front. At each generation of NSGA-II, non-dominated sorting is first employed to select solutions with lower ranks from the parent and offspring population, and crowding distance is used as the secondary metric to distinguish solutions in the same rank by favouring solutions with a large crowding distance. (Tian et al. 2017).

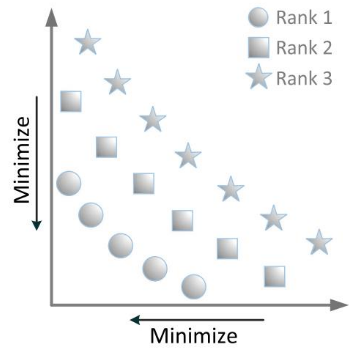


Figure 3: Illustration of non-dominated sorting with the population divided into three ranks (Tian et al. 2017)

Within the optimization tool, NSGA-II is utilized through Wallacei (Makki et al. 2019), an evolutionary engine that allows users to run evolutionary simulations in Grasshopper. Wallacei employs a simple user interface, as shown in Figure 4, to run the NSGA-II based on user-defined objective criteria and parameters. The engine can then be used to analyze the results and export phenotypes.

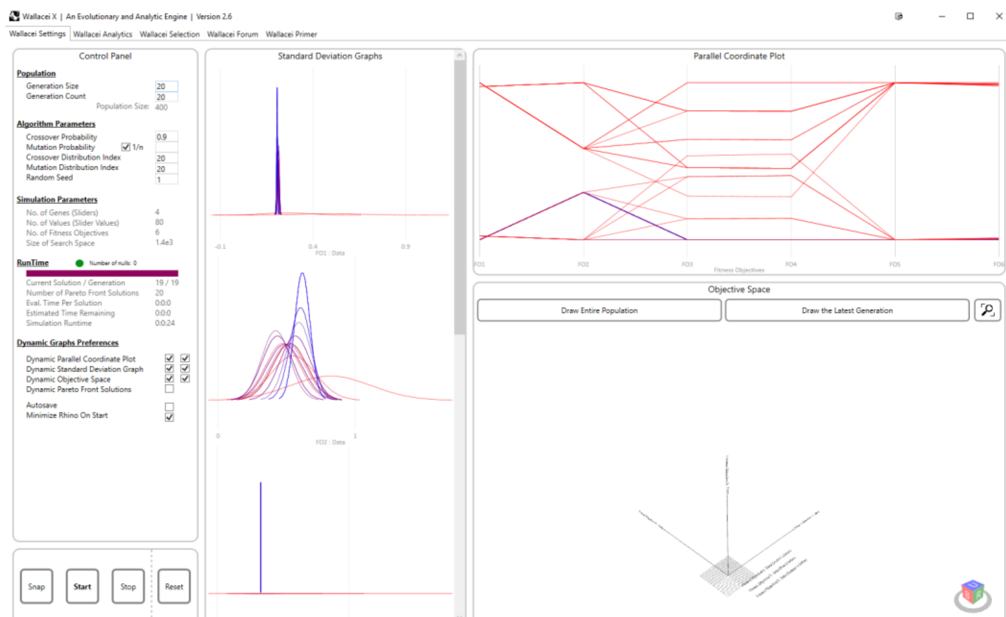


Figure 4: Wallacei evolutionary engine user interface

To use the evolutionary solver, the user must define a set of genes (parameters) and fitness objectives (optimization criteria). The fitness objectives are represented by values that the user aims to minimize. If the user wishes to maximize a fitness objective, the value must be inversed. For instance, if the user wishes to minimize the fitness objective x, the value should be represented as x. However, if the user wishes to maximize the fitness objective y, the value should be represented as 1/y. The accuracy and duration of the optimization process is determined by the generation size and count specified. Generation size refers to the number of offspring produced for every generation, while generation count refers to the number of generations produced overall. For example, if the user specifies a generation size of 20 and a generation count of 30, the total population produced will be 600. For every generation, the EA evaluates the populace against the defined fitness objectives. Offspring with parameters that favour the defined fitness objectives are crossbred together, while the others are discarded. This process is repeated for the specified generation count with the intent of producing a set of optimal solutions from which the user chooses the most appropriate solutions. Figure 5 showcases the individuals generated for a single generation during the optimization process of a shear end plate connection.

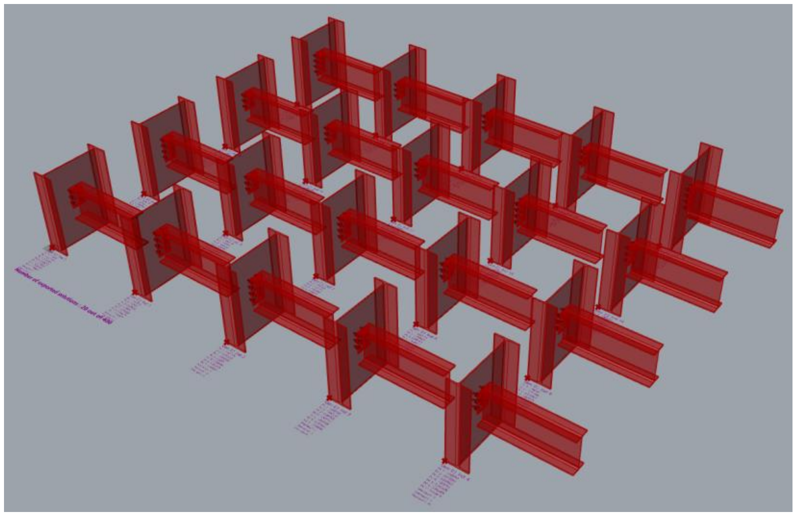


Figure 5: Solutions generated using the optimization tool for a shear end plate connection through Wallacei

2.4 Standards-based Solution (Limit States Design)

The optimization tool is split into two design methodologies: a standards-based solution using limit states design and a solution determined through CBFEM. The standards-based solution is derived from the provisions of CSA S16-19. Limit states that are not covered in CSA S16-19 are supplemented by equations defined in AISC 360-16 (AISC 2016).

Due to the simplistic nature of common shear connections, limit states design is relatively straight forward, requiring few computational resources for the evolutionary solver to generate a solution. This drastically decreases the overall optimization duration in comparison to the finite element (FE) based solution. However, the standards-based solution is limited to simple steel connections, as standards provisions may not be adequate for complex connections requiring design software.

The optimization criteria presented for the standards-based solution aims to maximize the demand-to-capacity ratio, while maintaining a ratio equal to or less than 1.0 to satisfy strength requirements.

2.5 Finite Element-based Solution

The FE-based solution of the optimization tool uses IDEA StatiCa (IDEA StatiCa 2021), a connection design software that utilizes CBFEM. CBFEM is a combination of the component method and the finite element method. The component method is a technique whereby components are individually modelled as complex springs that reflect the strength, stiffness, and deformation capacity of the component, and the behaviour of a joint can then be determined by assembling the individual components with help of mechanical models (Steenhuis et al. 1998). CBFEM removes the restrictions and most simplifications used in the component method. In CBFEM, plates are modelled by shell elements, while the components, e.g., bolts or welds, are modelled by nonlinear springs with their properties based on design codes and research. CBFEM provides code checks of failure modes that may not be captured by finite element analysis alone, such as weld fracture (Sabatka et al. 2014).

Although finite element analysis is a powerful analysis method for simple steel shear connections, the time required for the evolutionary solver to generate a single solution can become significantly greater in comparison to the standards-based solution. Similar to the standards-based solution, the optimization criteria presented for the FE-based solution aims to maximize the utilization ratio of the bolts and welds, and the plastic strain of the plate while remaining below a certain threshold to satisfy strength requirements.

3 SHEAR END PLATE CONNECTION CASE STUDY

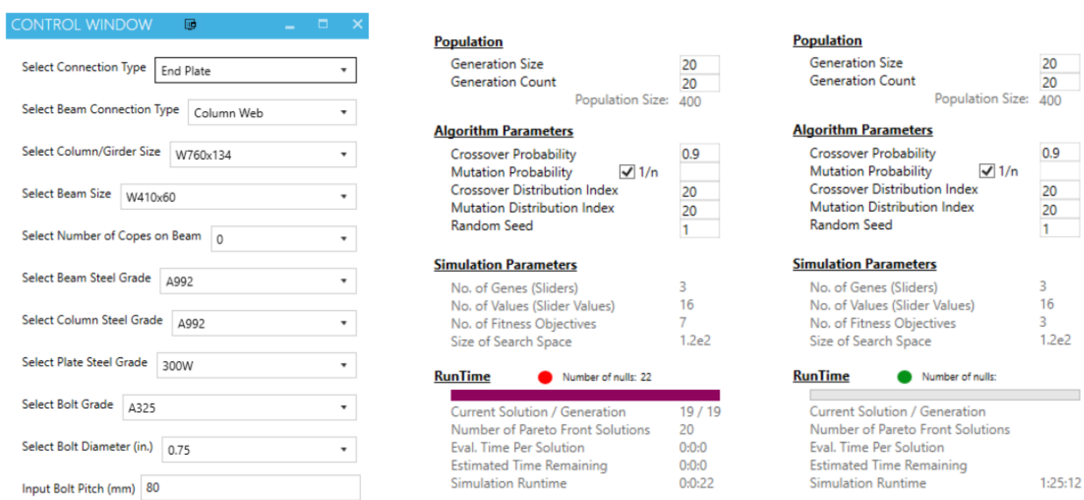
The optimization tool is used to design a shear end plate connection. The results are then be compared against the design from the Handbook of Steel Construction. The end plate connection consists of a W410x60 beam framing into the web of a W760x134 girder, both of ASTM A992 steel, with a factored reaction of 325 kN. The connection material consists of a G40.21 Grade 300W steel plate, ¾ in. (19.1 mm) diameter ASTM A325 bolts, and E49XX electrodes. Both the FE- and standards-based solutions are evaluated.

The end plate is assumed to have sheared edges with an edge distance rounded up to 35 mm. An 80 mm bolt pitch is used. Input parameters for the optimization tool are shown in Figure 6(a). The generation size and count are both set to 20. The plate thickness parameter ranges from 6 to 10 mm, as suggested by the Handbook of Steel Construction, to obtain adequate flexibility. Furthermore, the number of bolt rows range from 2 to 4, which is compatible with the bolt pitch and depth of the beam. Finally, the fillet weld size ranges from 3 mm to 10 mm. Although the minimum and maximum fillet weld sizes are constrained by parameters such as the end plate thickness and girder-web thickness, these constraints were ignored for this study to expand the search space of the EA.

3.1 Standards-based Solution Results

In the standards-based solution, the factored reaction is divided by each limit state capacity to obtain the demand-to-capacity ratio. The results are then inversed and any values below 1.0 are filtered out as null solutions, which are ignored by the EA. Thus, any connection design that the user exports from the optimization results will be one that satisfies strength requirements. It should be noted that implementing null solutions into the design problem should be avoided unless the user understands its origins. Optimization parameters used in the evolutionary solver are shown in Figure 6(b).

After the optimization is complete, the user can export any solution to display the resulting fitness values and parameters, as shown in Figure 7, wherein the three data inputs refer to the plate thickness (mm), number of bolt rows, and fillet weld size (mm), respectively. Every solution can be plotted onto a parallel coordinate plot, as shown in Figure 8. The solution highlighted in black in the figure represents the solution with the lowest average inversed demand-to-capacity ratio of all the limit states considered. This represents the solution with the highest demand-to-capacity ratio not exceeding 1.0. For this study, this solution is considered to be the optimal solution. The optimal design determined from the standards-based solution is an end plate connection with plate size PL170x6x230 mm, 3 rows of bolts with a gauge distance of 100mm.



(a) (b) (c)

Figure 6: (a) Parameters inputted in the user interface for the optimization process (b) Wallacei interface using the standards-based solution, (c) Wallacei interface using the FE-based solution

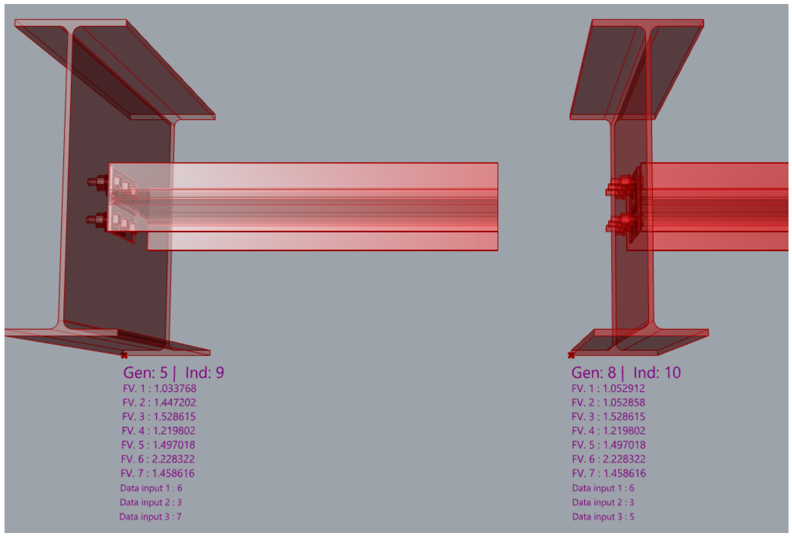


Figure 7: Fitness values and parameters of individuals generated through the standards-based solution

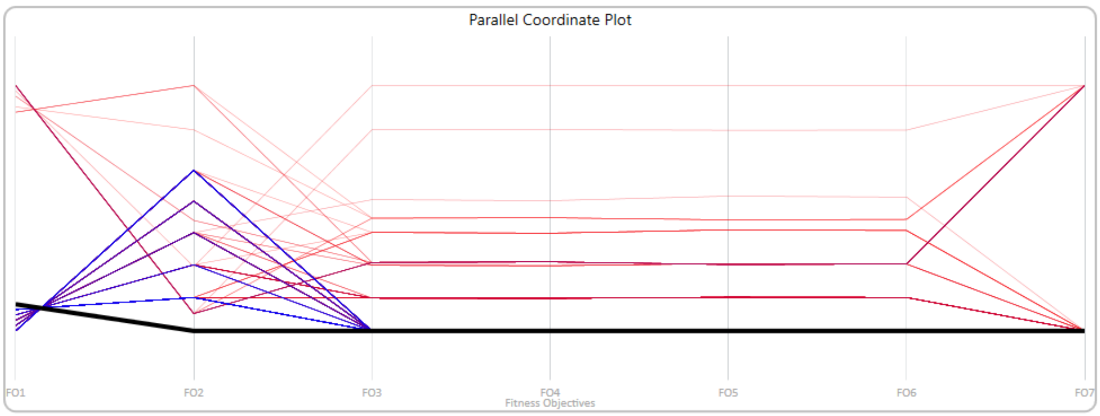


Figure 8: Parallel coordinate plot of the solutions generated through the standards-based solution

3.2 Finite Element-based Solution Results

The FE-based solution uses results from the connection design software to determine the fitness values. Three fitness objectives are defined for the FE-based solution including maximizing the plastic strain of the plate while remaining below 5%, maximizing the utilization of the bolts while remaining below 100%, and maximizing the utilization of the weld while remaining below 100%. The limiting value of 5% for the plastic strain is suggested in the Eurocode (CEN 2005). To quantify the fitness objective for the plate strain, the results are divided into 5, while any results below 1.0 are discarded. Similarly, to quantify the fitness objective for the bolt and weld utilization, the results are divided into 100, while any results below 1.0 are discarded. Optimization parameters for the FE-based solution are identical to those for the standards-based ones shown in Figure 6(c).

The parallel coordinate plot of the optimization process is shown in Figure 9. Similar to the standards-based solution, the optimal solution using the FE-based method is an end plate connection with plate size PL170x6x230 mm, 3 rows of bolts with a gauge distance of 100 mm, as shown in Figure 10.

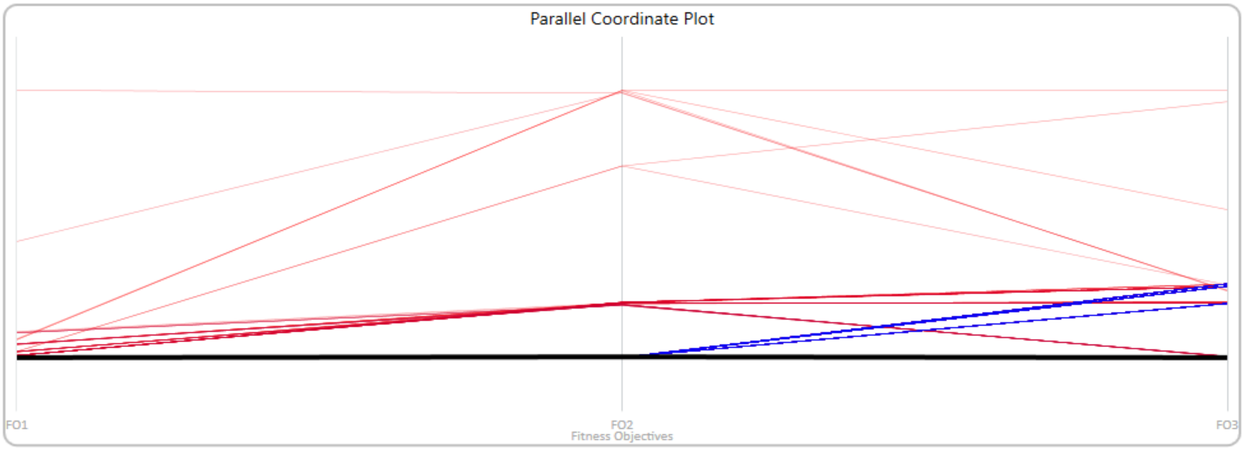


Figure 9: Parallel coordinate plot of every solution generated through the FE-based solution

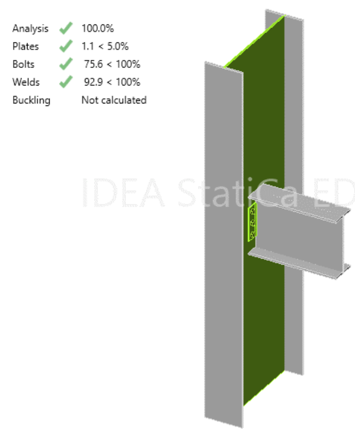


Figure 10: Verification of the optimal design of an end plate connection using IDEA StatiCa

3.3 Evaluation of Two Solution Approaches

It can be shown that even through a parametric study, the FE- and standards-based solution both result in the same answer given the same parameters and objective criteria. The solution in the example given in the Handbook of Steel Construction specifies a PL160x6x230 mm end plate connection. The difference between the solution obtained through the optimization tool and what is specified in the Handbook is the plate size. In the optimization tool, the plate is assumed to have sheared edges which requires a slightly larger edge distance, resulting in a larger plate width. Although the design given in the Handbook is not necessarily an optimized solution, it is encouraging that the results for both solutions match.

Even though the FE- and standards-based solutions gave an identical connection design, the optimization runtime for the standards-based solution was 22 seconds, while the runtime for the FE-based solution was more than 85 minutes, as shown in Figures 6(b) and 6(c). This indicates that the standards-based solution may be more favorable for such simple shear connections.

Ideally, MOPs should have thousands of generations and generation sizes to ensure that the optimization process converges to an optimal set of solutions. However, due to simplistic nature of the problem in this study, only a small number of individuals were generated: 400. It should be noted that the search space for this study includes only 120 possible solutions. This means that there are individuals produced with identical genes. However, this does not indicate that every possible solution was searched during the optimization process. As the EA searches for an optimal set of solution, Pareto optimal solutions can be the same if the gene pool is relatively small.

4 POTENTIAL AND DRAWBACKS

Although the shear end plate connection explored in this paper utilizes few parameters and a simple objective criterion, the proposed tool has the capability to parametrize additional connection details such as bolt pitch, edge distance, and add additional bolt columns. The objective criteria can also be expanded to reduce net fabrication and erection costs by considering material, labour, fabrication and erection constraints, machinery availability, and available inventory based on the steel fabricator’s preferences. All these additions can provide instant feedback to designers on how certain changes affect cost and constructability, while allowing for the automated design of connections.

By combining the optimization capabilities of EA with CBFEM, this tool can be extended to encompass more complex connections. Leveraging connection design software through this tool streamlines the design process as users only need to check the output of the connection design software. One drawback to using CBFEM for analysis is the long optimization time which would be increased for complex connections. This process, however, can be exported to external servers to be run on cloud computers, greatly reducing the optimization runtime, or the number of objective functions can be refined to achieve a more efficient design process. Increasing the efficiency of the software itself can also reduce the optimization runtime. For example, the software could be programmed to not fully analyze a solution if the early analysis results are not within a certain threshold.

Solving MOPs are not limited to NSGA-II; there are countless multi-objective EA and other algorithms that can be used to optimize structural steel connections. For example, the particle swarm optimization, an algorithm that mimics the unpredictable nature of a bird flock to determine an optimal solution (Eberhart and Shi. 2001), can also be used.

Additional add-ons such as integration of structural models to allow users to import member sizes and pass-through forces directly into the optimization tool can provide another level of automation to a typical connection design workflow. Connection designers could import, design, optimize, and export multiple optimal solutions that suit their preferences in a matter of minutes through an entirely automated process. This would aid in addressing the issue of constantly adjusting designs due to changes that arise throughout the life cycle of a project.

5 CONCLUSIONS AND FUTURE WORK

Automated optimization of structural steel connections can be achieved through evolutionary algorithms and parametric modelling. This paper focuses on the optimization of a shear end plate connection design through an optimization tool proposed here, which takes advantage of both limit states design and finite element modelling approaches. The results of the optimization of the shear end plate connection are nearly identical with the example end plate connection given in the Handbook of Steel Construction. Although only the demand-to-capacity ratio of the connection was optimized in this study, it showcases the application of generative design and EA within the steel construction industry. The advantages of using these optimization processes include reducing the number of re-designs during the lifecycle of a project, minimizing connection costs, reducing repetitive tasks in connection design, and providing designers with feedback on how certain changes affect other parameters within a steel connection.

Additional parameters should be added in future to better represent the realistic design process of a connection designer. With the help of Canadian steel fabricators and connection designers, additional objective criteria such as reducing material, crane operation, welding, labor, and energy costs can all be implemented into the tool. A case study can be performed in partnership with Canadian steel fabricators to verify optimization results and determine the applications of this optimization tool in industry practice. Implementation of the ability to export joints from structural models can also further automate connection design, drastically improving the typical workflow. This tool can finally be extended to encompass utilizing other AI techniques and compare the optimization speed between different algorithms.

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