

Beyond optimality: Genetic Algorithms and Fuzzy Inference for Coil-Order allocation in the steel industry.

Marco Vannucci* Valentina Colla* Laura Laid*
Erwin Sirovnik**

* *TeCIP institute, Scuola Superiore Sant'Anna, Pisa, Italy (e-mail: marco.vannucci@santannapisa.it ; valentina.colla@santannapisa.it ; laura.laid@santannapisa.it).*

** *Thyssenkrupp Rasselstein GmbH, Andernach, Germany (e-mail: erwin.sivornik@thyssenkrupp.com)*

Abstract: The paper addresses the Coil-Order Allocation problem in steel industry via Genetic Algorithms through two approaches: a basic solution with a standard objective function and an advanced method incorporating a Fuzzy Inference System to mimic human decision-making. Both solutions were tested on real-world data from a tinplate production plant, achieving significant improvements in orders fulfillment and material utilization compared to manual allocation. The basic genetic approach outperforms the baseline in efficiency, while the fuzzy-genetic method demonstrate flexibility for complex, customizable optimization. The results show the potential of combining heuristic techniques and fuzzy logic to enhance industrial operations.

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1. INTRODUCTION

The Coil-Order Allocation (COA) problem represents a significant challenge for steel industry, where steel coils must be assigned to customer orders in an efficient and cost-effective manner and must be delivered on time. Each steel coil is characterized by specific dimensions, material properties, and quality grades, while customer orders come with detailed requirements such as width, thickness, weight, and surface quality. The allocation process involves finding optimal combinations of coils that meet these requirements while minimizing waste, such as leftover material or trims, and adhering to production constraints.

This problem is inherently complex due to the diversity of order specifications, which can widely vary in terms of size, quality, and quantity. Moreover, inventory constraints often imply that the coils available in stock may not perfectly align with the needs of specific orders, necessitating substitutions or adjustments. The process is further complicated by the need to balance multiple operational objectives, such as minimizing material waste, reducing processing times, and ensuring a fair distribution of resources among customers. Dynamic factors, e.g. changes in inventory levels, shifting order priorities, and evolving production schedules, add an extra layer of complexity.

Developing efficient solutions to this problem is crucial for enhancing profitability and maintaining competitiveness in the steel industry. Given the complexity of the task, the many criteria to be considered, modern approaches leverage artificial intelligence, heuristic optimization techniques, and machine learning to address the challenges and

achieve an effective balance between customer satisfaction and operational efficiency.

Heuristic approaches including Genetic Algorithms (GA) have been used in recent years to handle interactions between different criteria. In Zou et al. (2023), the authors propose a model for the allocation of coil orders, dealing with dynamic events and time constraints. The solution uses evolutionary optimisation to address real-time production requirements. Similarly, in Zou et al. (2017) a differential evolution algorithm is proposed for the dynamic management of open orders in production, including aspects of production scheduling. In other works, previsual aspects are combined, as in Zou et al. (2020) and Zheng et al. (2022) where predictive models based on neural networks is used for production estimation in order to dynamically optimise a multi-objective COA problem.

This paper addresses COA via GA through two approaches: a standard method and an enhanced one, which incorporates a Fuzzy Inference System (FIS) to the aim of integrating evaluation criteria and decision-making processes akin to those used by human operators into the optimization process. The two approaches are tested on a real-world case study and compared against the standard allocation performed by plant operators.

The paper is organised as follows: Sec. 2 presents the case study, while in Sec. 3 the two approaches are motivated and described in detail. Their achievements are reported in Sec. 4 where they are discussed and compared to standard operation. Sec. 5 provides concluding remarks and future perspectives for the proposed approaches.

2. CASE STUDY

The Rasselstein plant in Andernach, Germany, is specialized in producing tinplate, a type of flat steel product primarily used in packaging industry. Its production is focused on continuous processing methods to manufacture high-quality tin-coated and chrome-coated steel coils. These coils are then used for the manufacturing of diverse types of goods such as food cans, steel boxes, twist-off caps and closures and many other packaging solutions that require durable materials. The plant is the largest in the world for tinplate production, ensuring high-capacity and precision manufacturing to meet global demand.

In the daily production process, the COA issue is a significant operational challenge at the plant, given the high volume of coils produced daily to meet customer orders. Among these, some coils are rejected at various production stages due to quality issues, such as surface defects. Consequently, experienced plant personnel must manually allocate coils to orders, navigating a complex decision-making process that involves balancing multiple constraints and objectives, including order specifications, production priorities, and quality standards. This task is critical to ensure order fulfillment while minimizing waste and optimizing production efficiency. In the context of the case study, the conditions governing the eligibility of a coil for assignment to a specific order are numerous and diverse, and can be categorized as follows:

- **Steel Grade:** Each order specifies a required grade of steel to meet its technical and performance standards.
- **Dimensions:** Orders demand coils with precise width and thickness specifications to comply with design or processing requirements.
- **Coil Weight:** A specified weight range must be adhered to for each coil associated with the order to optimize handling and further processing.
- **Hot-Rolling Mill (HRM):** Certain orders may require coils to be processed through a designated hot-rolling mill line to ensure uniformity or meet specific technical criteria.
- **Provenance:** Orders may mandate a specific origin for the coil, reflecting prior processing steps or certification needs.

These constraints - that must be jointly fulfilled to assign a coil to a specific order - form the foundation of the allocation process, ensuring that orders are fulfilled while adhering to quality, compatibility, and operational requirements. During the allocation phase, operators must primarily consider two key objectives:

- **Material Allocation vs. Order Demand,** i.e. minimization of the discrepancy between the material requested and the material actually allocated to each order. Achieving this objective requires careful planning to optimize the use of available coils while meeting customer expectations.
- **Order Delivery Deadlines,** i.e. adherence to delivery schedules. Operators prioritize orders based on their deadlines, with earlier deadlines receiving higher priority in the allocation process.

Secondary factors, while not primary, also affect allocation prioritization. This includes, for instance, the logistics

route for the final products. It makes a difference whether a fixed shipping date for overseas customers must be met or there is a certain flexibility with the truck.

The problem outlined above is addressed in this paper through the application of various optimization approaches, leveraging a comprehensive dataset provided by Rasselstein. This dataset, directly sourced from the plant, offers a realistic snapshot of the daily challenges faced by operators. It encompasses approximately 1000 orders and around 4000 coils available for allocation. These orders and coils exhibit significant diversity in terms of dimensions, steel grades, and weights. However, due to confidentiality constraints, further details on these characteristics cannot be disclosed. In many cases, as is typical in practical scenarios, the available coils are insufficient to fully meet the demands of all orders, necessitating a strategic allocation process to maximize efficiency and order fulfilment.

3. GENETIC ALGORITHMS FOR COIL-ORDER ALLOCATION

The case study concerning the COA described in section 2 through its main operational constraints and objectives is addressed by using two different approaches that rely on heuristic optimisation methods. The first approach uses GAs in the context of the minimization of a standard and quite simple objective function, whilst the other one minimizes a more complex, highly non-linear objective function that embeds human reasoning through a FIS.

GAs are an optimization and search techniques inspired by the process of natural selection in biological evolution, which are largely applied for optimization in many industrial domains, such as data processing Catani et al. (2011), quality management Wang et al. (2024) and maintenance Qin et al. (2022). They operate by mimicking principles such as selection, crossover, and mutation to evolve solutions to complex problems. A population of candidate solutions, called individuals, is encoded as strings (analogous to chromosomes) and iteratively improved. The fittest individuals, based on an objective function called *fitness*, are selected to create the next generation through recombination and random alterations. Over successive generations, the algorithm converges toward an optimal or near-optimal solution. GAs are widely used in fields like engineering and optimization for their adaptability and robustness Sanchez et al. (2012).

GAs and heuristic methods in general offer several advantages over standard optimization approaches for solving Binary Integer Linear Programming (BILP) problems Kuendee and Janjarassuk (2018) Wasanapradit et al. (2011). These methods are particularly effective in handling the non-linearity and complexity inherent in such problems, as they explore large search spaces more efficiently without the computational burden of exact methods. They scale better for large problems, where traditional solvers may struggle with exponential increases in computation time. Unlike standard optimization techniques, which can become trapped in local optima, GAs use mechanisms like mutation and crossover to explore diverse regions of the solution space and find better approximations. Moreover, GAs are highly flexible, accommodating non-linear objectives or unconventional constraints

that are difficult for traditional solvers to handle. They inherently support parallelism by evaluating multiple solutions simultaneously, which is advantageous for distributed computing and tackling high-dimensional problems. Unlike exact methods, GAs require minimal problem-specific knowledge. They are also robust in dynamic or uncertain environments, adapting to changing constraints or objectives without needing to restart the process. Lastly, GAs are often simpler to implement for complex domains, offering a practical alternative to customizing traditional optimization algorithms.

3.1 Standard Genetic Algorithms based approach

Both GAs-based methods leverage on the evolution of candidate solutions that are compatible with the constraints described in Sec. 2. A solution consists of a set of associations between coils and orders. In more detail, given C the set of available coils where the generic coil is denoted c_i and given O the set of orders to be satisfied, where the generic order is denoted o_j , a candidate solution S will be a set coil-order associations as follows:

$$S = \{(c_i, o_j) \mid c_i \in C, o_j \in O\} \quad (1)$$

where a generic coil c_i can be associated with at most one order (or remain unallocated), while a single order o_j is associated to more than one coil as defined in Eq. 2:

$$\forall (c_i, o_j), (c_k, o_l) \in S, c_i = c_k \implies (c_i, o_j) = (c_k, o_l). \quad (2)$$

All coil-order associations within S must comply with the operational constraints encapsulated in the Coil-Order Binary Association Matrix (COBAM). COBAM is a binary matrix of dimensions $M \times N$, where M represents the number of coils and N the number of orders (normally $M \geq N$, and often $M \gg N$). Each element $COBAM_{i,j}$ is set to 1 if coil c_i satisfies all constraints required to associate it with order o_j , 0 otherwise. In the implementation of the optimizer, a generic solution is represented as an array of M elements (one for each coil). Each element in the array either contains the ID of the order it is allocated to (in accordance with COBAM) or the *None* value, signifying that the coil is not assigned to any order. The initial population of solutions is randomly generated by creating P solutions that respect operational constraints (P is one of the hyper-parameters of the optimization). Specifically, a generic feasible solution is formed by assigning for each element (representing a coil), the value of one of the order IDs for which the associated COBAM value is 1, or the *None* value.

The *crossover* operator in the adopted GA implementation generates a child solution from two parent solutions. Each element of the child solution is determined by randomly taking the value of the corresponding element from one of the two parents. This implementation respects the constraints of COBAM by construction. The *mutation* operator changes a part of the solution within the current generation, by randomly selecting a fraction (currently 10%) of its elements (called *genes* in the GA slang) to be mutated. These elements represent the associations of as many coils to orders and are mutated by picking an

alternative order chosen at random from those that fulfil the operation constraints according to the COBAM.

The *selection* function employs the *roulette-wheel* method, where individuals are probabilistically selected based on their fitness. Solutions with higher fitness values have a greater likelihood of being chosen, reflecting their relative quality within the population.

The *fitness* function is central to optimization using GAs, as it evaluates the quality of candidate solutions. In the adopted GA framework, optimization is performed by minimizing the objective function; candidate solutions with lower fitness values are favored. This choice does not affect the general applicability of the approach.

In this basic-GA method, the fitness function comprises two primary components. The first one addresses the relative discrepancy (D_j) between the required weight for an arbitrary order o_j and the total weight of the coils assigned to it, and is formally expressed as follows:

$$D_j = \frac{\left| \left(\sum_{c_i \mid (c_i, o_j) \in S} W(c_i) \right) - RW(o_j) \right|}{RW(o_j)} \quad (3)$$

where $W(c_i)$ is the weight of an arbitrary coil c_i and $RW(o_j)$ the weight requested to complete the order o_j . The absolute value operator was used in equation 3 to neutralize the sign effect, giving in practice the same importance to the lack and the surplus of allocated material.

The second part concerns the prioritisation of orders in terms of Days to Due-date (DDS). In this context, orders with the earliest due date have priority over the others. This relationship is expressed as:

$$P_j = \left(\frac{\max(DDS) - DDS_j}{\sum_j DDS_j} \right)^2 \quad (4)$$

where DDS is the array of the days to due-date for all orders, and DDS_j refer to the j -th order. The denominator of Eq. 4 plays a normalising role to get values of P_j in the range (0,1). The priority weight P_j increases as the order due-date gets close to 0. If the due-date is past and the order was not satisfied on time, then $P_j = 2$. The exponent 2 used in the formula was determined empirically in order to stabilise its behaviour.

The final fitness function for a solution S combines these two components, as follows

$$fitness(S) = \sum_{o_j \in O} D_j \cdot P_j \quad (5)$$

According to Eq. 5 the optimization process minimizes the total weight discrepancies between the required and allocated steel for each batch order. These discrepancies are weighted based on their priority, which is determined by the proximity to the respective due dates of the orders.

3.2 Genetic Algorithms minimizing a Fuzzy-Inference based objective function

A more advanced and comprehensive approach to addressing the COA problem involves leveraging a FIS as the

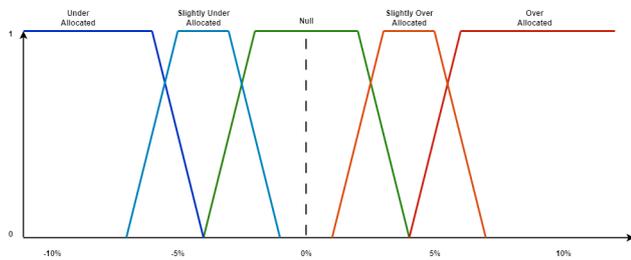


Fig. 1. Membership functions for the 5 fuzzy sets composing the **percent weight discrepancy** (PWD) fuzzy variable.

objective function to be minimized by the GA optimizer. This method integrates the distinctive features of human reasoning, including the ability to handle uncertainty, abstract concepts, and incorporate qualitative experience. By doing so, it overcomes the rigidity of purely mathematical formulations, such as that represented by Eq.s 3, 4 and 5, enabling a richer, more flexible and more intuitive optimization framework. This approach uses a rule-based system grounded in human knowledge and experience, expressed through natural language, while still incorporating the two fundamental criteria of the standard approach: weight discrepancy and days to due-date.

The adoption of a FIS to combine several criteria, as shown in Cateni et al. (2017), allows for the design of a more complex, highly non-linear objective function that is easily extendable and customizable. Due to its nonlinearity, standard optimization algorithms such as BILP and ILP cannot be effectively employed for its minimization, making heuristic methods like GAs more suitable for the task. Each of the two main criteria (now called *fuzzy variables* in the vocabulary of fuzzy reasoning) is associated to a list of *fuzzy-sets*. Each fuzzy set describes a qualitative state or range of the fuzzy variable. A fuzzy set is defined by a *membership function*, which assigns a degree of membership (ranging from 0 to 1) to each possible value of the fuzzy variable. For the allocated-to-requested weight discrepancy of each order (previously referred to as the D_j criterion), 5 fuzzy sets are defined, ranging from *under-allocated* to *over-allocated*, as shown in Fig. 1. This figure also depicts the shapes of the corresponding membership functions within a percentage-based domain. Order punctuality (formerly denoted as DDS_j) is modelled using 3 fuzzy sets, with their associated membership functions presented in Fig.2. These fuzzy sets represent different scenarios, including delayed delivery, on-time delivery, and early readiness and map the domain of the days to due-date of each order.

The fuzzy variables are used in the antecedents of a rule set designed to assess the allocation of an individual order. The evaluation result is also represented as a fuzzy variable EVAL defined on the domain $[0, 100]$, over which 3 fuzzy sets -low, average, and high - are defined to describe the quality of the solution (see Fig. 3).

The FIS used to evaluate the allocation of individual orders and which exploits the fuzzy variables shown is composed of 9 IF-THEN rules that relate the input variables (discrepancy and punctuality) to the evaluation of each order. The rules are shown here below using some

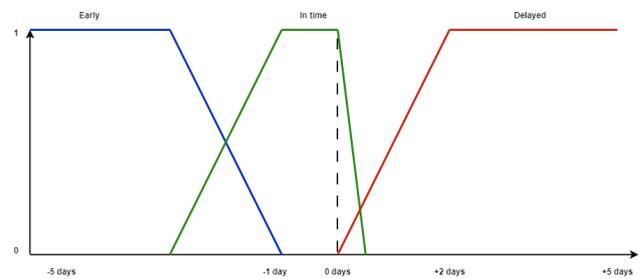


Fig. 2. Membership functions for the 3 fuzzy sets composing the **days to due-date** (DDS) fuzzy variable.

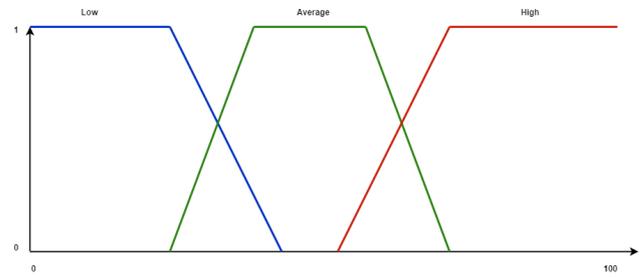


Fig. 3. Membership functions for the 3 fuzzy sets composing the **evaluation** (EVAL) fuzzy variable.

abbreviations of the names of the employed fuzzy sets (i.e. *SUA* stands for *Slightly Under Allocated*).

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IF PWD is NULL AND DDS is INTIME THEN EVAL is H,
IF PWD is OA THEN EVAL is L,
IF PWD is UA THEN EVAL is L,
IF PWD is NULL AND DDS is EARLY THEN EVAL is H,
IF PWD is NULL AND DDS is DELAY THEN EVAL is A,
IF PWD is SOA AND DDS is INTIME THEN EVAL is A,
IF PWD is SUA AND DDS is INTIME THEN EVAL is H,
IF PWD is SOA AND DDS is DELAY THEN EVAL is L,
IF PWD is SUA AND DDS is EARLY THEN EVAL is A,

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Given a solution to the COA problem coded for GA-based optimization as in Eq.s 1 and 2, its fitness is calculated as the average of the evaluations through the FIS of the individual order allocations, as follows:

$$fuzzyFitness(S) = 100 - \frac{\sum_{o_j \in O} FIS(Alloc_j)}{N} \quad (6)$$

where N is the total number of orders, $Alloc_j$ the allocation of the coils for an arbitrary order o_j and the -100 factor is used to adapt to the minimization nature of the employed GA framework. The evaluation of individual order allocation goodness is computed according to the standard steps for the FIS evaluation, namely fuzzyfication of input variables, rules application, aggregation of the rules output and defuzzification. In detail, the configuration of the entire rule evaluation process is standard: the logical AND operator is calculated as the **minimum** of the degrees of membership of the antecedents, aggregation uses the **sum** method to represent at best all rules involved, while defuzzification uses the **centroid** method. Except for the employed fitness function, all other GA operators,

solution coding and hyperparameters are identical to those described in Sec. 3.1.

4. EXPERIMENTAL SET-UP AND RESULTS

The two approaches described in Se. 3 were applied to solve the COA problem described in Sec. 2, and operate within a shared optimization framework. This proprietary framework is built on an adaptive GA proposed by Vannucci and Colla (2015), designed to achieve faster convergence compared to standard implementations while effectively avoiding local minima, as evidenced by its success in various industrial applications as shown in Vannucci et al. (2016). For both approaches, the GA components, such as recombination functions and hyper-parameters, are identical. The hyper-parameters were empirically determined, by selecting configurations that optimize both objective function value and computation time. The GA population size is set to 100 chromosomes with a maximum of 500 generations allowed for convergence, but the algorithm employs a parameter named *patience*, which limits the number of consecutive generations without improvement to 50. Recombination rates are dynamically adjusted throughout the optimization process, in line with the adaptive nature of the chosen GA implementation, while the value of the *Elite* parameter is set to 1.

In the considered case study, GA runs reach quite fast convergence. The whole optimization process requires less than 4 minutes. The goodness of the proposed solutions is measured according to industrial Key Performance Indicators (KPIs): the main drivers are the number of completed orders and the average discrepancy between allocated and requested weight throughout the orders. The obtained KPI values for the baseline case (human allocation) and the two GA-based approaches are shown in Tab. 1 .

Table 1. Achievements of the optimized COA in comparison to the human based one.

	Baseline	GA-Standard	GA-Fuzzy
Completed orders, %	54	69	69
Ave. discrepancy, %	4.7	3.2	3.8
Ave. discrepancy, tons	3.5	2	2.3

The results demonstrate the significant improvements can be achieved through the proposed optimization techniques, with the standard GA-based approach slightly outperforming the one coupling GA and FIS. This outcome aligns with expectations, as GA-Basic explicitly optimizes an objective function closely linked to the minimization of weight discrepancy. From a quantitative perspective, GA-standard yields substantial benefits compared to the baseline, as it increases the number of completed orders by 27% and reduces the average relative discrepancy between the required and allocated steel for orders by 1.5 percentage points. This reduction is evident in Fig. 4, which shows the percent discrepancy for the whole set of managed orders for the baseline and the standard GA-based approaches. Such achievement is particularly critical for enhancing customer satisfaction and achieving material savings. The improvement relevance is illustrated in Fig. 5, which shows the distribution of relative discrepancies. Notably, in the baseline scenario, the distribution exhibits a skewed quasi-Gaussian shape biased toward surplus material. This surplus translates into unnecessary material waste, which

implies significant inefficiencies from the manufacturer’s perspective. The figure also shows that this improvement is valid for both GA-based approaches.

The GA-Standard method emerges as the best performing approach across all the evaluated criteria, but the GA-Fuzzy method shows comparable performance and significantly outperforms the baseline scenario involving manual allocation. The primary advantage of the GA-Fuzzy method lies in its flexibility, which allows full customization of the objective function. This customization enables seamless incorporation of additional criteria, rules, or uncertainties without imposing the formulation of linear constraints. Furthermore, these adjustments require minimal implementation effort and can often be automated, making the GA-Fuzzy approach particularly suitable to dynamic or complex optimization scenarios. This flexibility, combined with the ability to capture the nuances of human reasoning, makes this method highly appealing in contexts such as COA. It enables development of solutions that transcend rigid, although efficient, mathematical formulations, offering a more adaptive and holistic approach that extends beyond traditional optimization.

5. CONCLUSIONS AND FUTURE WORK

Two GA-based approaches to the COA problem in the steel industry have been presented: a basic approach using a standard objective function and an advanced method using a FIS. Both methods demonstrated significant improvements over the baseline manual allocation. The GA-Basic method yields the best results, leading to substantial reductions of material discrepancies and relevant increase in number of completed orders. However, the GA-Fuzzy approach provided comparable performance while offering enhanced flexibility to adapt the optimization process to additional criteria or uncertainties. The findings emphasize the potential of heuristic optimization methods like GAs to improve operational efficiency and customer satisfaction in complex industrial settings. Moreover, the integration of fuzzy logic into optimization frameworks appears a promising way to incorporate human reasoning into automated decision-making processes. Future work will focus on extending the flexibility of the FIS-based GA approach by integrating more sophisticated criteria, such as dynamic cost considerations and real-time constraints, to further enhance its applicability to dynamic production environments. Additionally, the development of hybrid optimization frameworks combining GAs with other machine learning techniques will be explored to achieve even better performance in solving complex allocation problems.

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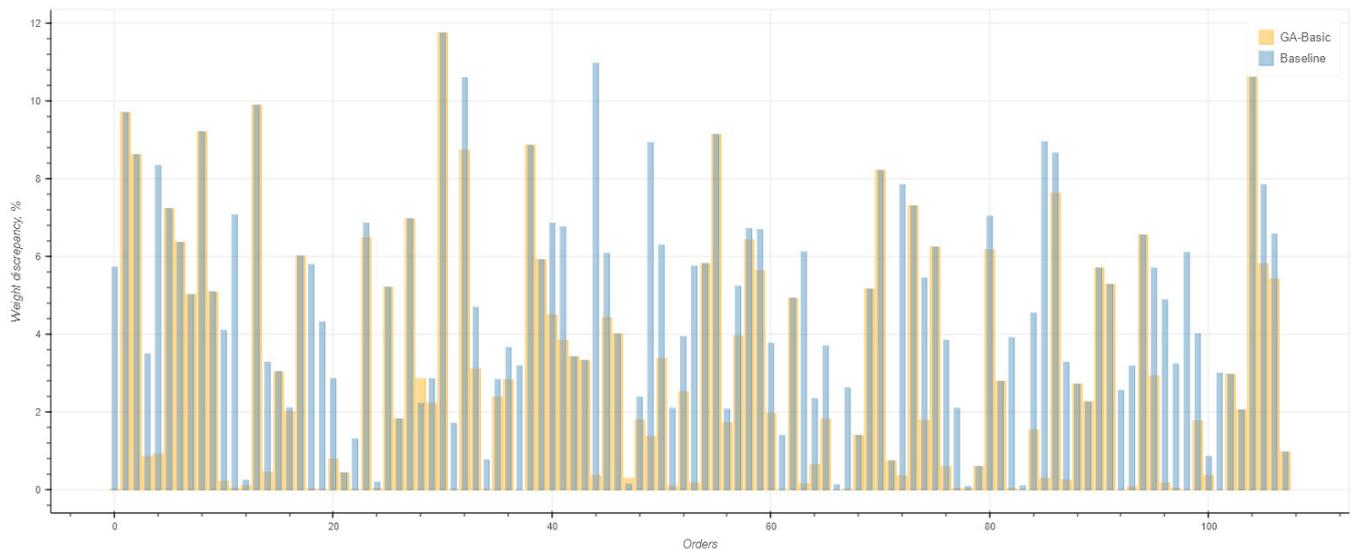


Fig. 4. Percent discrepancy between allocated and requested steel weight for the managed orders within the case study for Baseline and GA-Basic approaches.

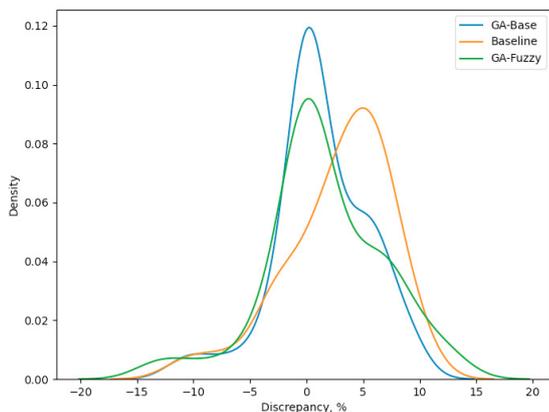


Fig. 5. Distribution of the percentual discrepancy between allocated and requested steel weight for the managed orders within the case study for the baseline human allocation and the optimized approaches.

for any use that may be made of the information contained therein.

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