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Surface Integrity Analysis of Wire Electric Discharge Machining of Nitinol Shape Memory Alloy: A Literature Review

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When nitinol is machined, quantitative details regarding the surfaces such as the surface crack density, utmost peak-to-valley heights, recast layer thickness and the mean peak-to-valley height among others offer the most appropriate features to consider in the integrity of the surfaces of machined nitinol. This quantitative information directs the integrity and the projected future performance of the machined nitinol in the components. Consequently, the research question of how to achieve optimal surface integrity of the machined nitinol is important. A literature review is conducted to study the surface integrity analysis of wire electrical discharged machined nitinol. In particular, published papers between 2007 and 2021 have been reviewed. Literature is explored concerning the method of analysis, parameters of research interest and the problems/issues arising from the literature. Diverse methods were employed to evaluate the surface integrity of nitinol after machining. Commonly, both mathematical optimization and microstructural characterizations are used to suggest ideas. Mathematical optimization has been in two broad perspectives, namely, experimental design-based methods such as orthogonal arrays, signal-to-noise ratios, Taguchi's utility and quality loss function, Box-Behnken design and response surface methodology. The non-traditional optimization schemes such as the differential evolution, multi-objective optimization based on ratio analysis and teaching learning-based optimization have been applied. For microstructural characterization, tools to evaluate the surface integrity of nitinol such as field emission scanning electron microscope and energy dispersive X-ray have been deployed. Parameters such as residual stress, geometric deviation, microhardness and profile accuracy are pursued to be optimized. It is known that various literature reviews in previous years have studied the surface integrity problem of nitinol using large-scale approaches. However, in this article, a brief review is prescribed and this work reveals how the surface integrity analysis of nitinol has been tackled in the literature.

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1. INTRODUCTION

In the present age, component users demand high product quality and improvements. Drives are always being pursued by nitinol-based component manufacturers for excellence in manufacturing (Kedare et al., 2018). However, recently, understanding the changes in the conditions of the nitinol material surfaces is a timely discussion in both surface science and product development agendas. A pivotal aspect of nitinol WEDM for understanding and applying surface science and engineering principles while manufacturing components are surface integrity analysis. Surface integrity is defined as the inbuilt and superior state of the nitinol's surface generated during machining on the WEDM. Research has established a strong correlation between the surface layer characteristics and the mechanical features of nitinol SMA (Takale and Chougule, 2019), Chaudhari et al., 2020a, b; Majumder and Maity, 2018). Conventionally, the surface integrity analysis of nitinol involves the two principal views of surface layer attributes and topography attributes. While the surface layer attributes are often specified regarding tangential velocity (using huge normal gradients) and huge intensity gradients of substances (such as moisture and temperature) conveyed from or to the interface), the topography attributes are usually described in form of waviness, flaws, surface roughness and errors of form. The use of surface integrity principles in nitinol SMA manufacturing is promising principally for the following reasons. First, surface integrity showcases the effects of surface attributes and states that the nitinol SMA will possibly function. Second, it satisfies the growing requests for complicated parts performance. Third, the longevity of parts made from nitinol is often desired and the surface integrity analysis is an avenue to attaining this. Fourth, with an increasing drive towards miniaturization, surface integrity analysis is a medium to assist in its attainment. Fifth, the reliability of parts made from nitinol is of importance to the users and the drive towards surface integrity enhancement is in the direction of attaining this goal.

To the best of our knowledge, comparatively few investigations have discussed the surface integrity analysis of nitinol regarding cost and the death of information available on surface integrity analysis is a demotivating factor toward expanding the knowledge frontier of surface integrity analysis of nitinol. At present, the focus has been on surface morphology evaluation of the process parameters of nitinol, among others. Knowledge of the surface morphology is then used to improve the surface integrity of nitinol. However, focusing on the parametric analysis using surface morphology attributes of nitinol could no longer satisfy the requirement for excellent improvement in the surface integrity of nitinol. This is because of the following restrictions: (1) There are several hundreds of components to be manufactured using nitinol, which make the surface integrity improvement task for nitinol a huge challenge to tackle; (2) the complication involved in the surface integrity problem for nitinol trigger a huge difficulty for process engineers and operators of machine centres and drives them to fully utilize the scarce resources available to them for the nitinol-based manufacturing process. Consequently, there is an urgent requirement to install a programme that will ensure the judicious resource utilization and optimum performance of nitinol-based components. Thus, in this article, a research gap that shows pointers to optimization and prioritization concepts regarding the surface integrity process parameters is revealed. What needs to be tackled in the literature is the development of a coupled method of Taguchi and Pareto analysis with the ABC classification scheme as the Taguchi-Pareto and Taguchi-ABC methods. The results may be improved by introducing the Grey Wolf Optimizer to couple the Taguchi-Pareto, Taguchi-ABC and the Grey Wolf Optimizer.

Furthermore, in the engineering literature, several studies have revealed the potential of Pareto principles and the ABC classification scheme to enhance the optimization and prioritization of the Taguchi method combined with each of these methods. Together, the present article suggests that initiating a scheme of integrating the Taguchi-Pareto and Taguchi-ABC methods with metaheuristics such as the Grey Wolf Optimizer is a potential substantial intervention point to advance multi-modal integration in optimization while prioritizing the parameters of interest. Besides, optimization is an essential topic in machining ideas and it eventually influences the level that machine shops deliver machining performance. Optimization of machining processes and parameters is regarded as an essential requirement to respond to lean manufacturing idea that promotes judicious resources utilization in the machining shop. This need stimulates researchers and practitioners to expand the research horizon from optimization to an integrated optimization and prioritization scheme whereby an initially prioritized factor group into ranks through the delta values using the Taguchi method is further enhanced by the Pareto prioritization scheme and the ABC classification scheme. At present, researchers use integrated Taguchi-Pareto and Taguchi-ABC methods as means of concurrent optimization and prioritization in machining schemes. However, while this gap remains unattended in the literature, the real research gap promoted in the present article is to integrate the Grey Wolf Optimizer with either Taguchi-Pareto or Taguchi-ABC methods as Taguchi-Pareto Grey Wolf Optimizer-desirability function or Taguchi-ABC grey wolf optimization. By referring to previous studies on Taguchi-Pareto and Taguchi-ABC methods, the suggested titles to study in future research, containing an integrated Grey Wolf Optimizer can become a method to enhance the performance of nitinol-based components from the surface integrity analysis perspective.

2. THE DISCOVERY ACCOUNT OF NITINOL AND ITS ATTRIBUTES

In the year 1932, Arne Olander discovered the first shape memory alloy (SMA), and in 1960, the alloy nitinol (Nickel and Titanium alloy prepared in the Naval Ordnance Laboratory) was synthesized by Wiley and Buheler (Mubeen & Ahmad, 2021). The most notable property of SMAs is their ability to regain their original shape when heated after being deformed. nitinol stands out among other SMAs because of its comparatively low cost in production, straightforward handling safety, and superior mechanical characteristics (Chaudhari et al., 2021; Deng et al., 2021). Nitinol-60 also has some other very desirable attributes including elevated strength, corrosion confrontation, good electrical conductivity, and low thermal conductivity. The characteristics, however, make WEDM a great fit for a choice of the machining process, because conventional machining methods produce sub-optimal surface finishes and the tools used suffer wear.

3. FOCUS OF RESEARCH WORK

In this summary, the research was conducted to identify the important themes of discussion in the surface integrity domain of research while processing nitinol in the WEDM facility. To the present investigators, these themes could be summarized as the focus of researchers and they have important implications for the future of research on surface integrity while processing nitinol. In the study of WEDM of nitinol-60 SMA, the common aim is the optimization of the WEDM process, although different approaches are taken. Most studies focus on the optimization of some process parameters suspected to provide optimal process results. The research carried out by Chaudhari et al. (2021) focuses on the optimization of machining performance with the use of multi-walled carbon nanotubes (MWCNTs). Esteves et al. (2021) sought to characterize the dimensions of the craters that are formed in the erosion of material in WEDM.

Similarly, Majumder & Maity (2018) conducted research to compare and predict the machinability aspects of the material to find an optimum combination of process parameters that would yield the best results. Likewise, multi-objective response optimization was the central theme of the study carried out by Sharma et al. (2021a), although the material studied was the Alloy-706. While Kulkarni et al. (2018) sought to optimize the WEDM process as well; the research carried out was also geared towards identifying the most significant input parameter in the achievement of optimal output results.

4. PARAMETERS CONSIDERED

The parameters of the WEDM process while manufacturing nitinol show the most important elements of the process and are quantitatively described. In this section, they are described as important parts of the WEDM process. Input parameters are the elements that are transformed to produce the tangible outcome of the nitinol material processing system. Similar to standard manufacturing systems, the nitinol

WEDM process has outputs desired from the expected values. Thus, this section elaborates on the inputs and outputs of the nitinol-based component manufacturing system. The parameters in studying any process are classified as either input or output parameters. The input parameters can also be referred to mathematically as the independent variables, whose values have effects on the dependent variables. Likewise, the output parameters may be mathematically referred to as dependent variables, whose values are influenced by the input parameters/independent variables.

Input Parameters

One of the more common input parameters thought to affect the WEDM process is the pulse duration. Majumder & Maity (2018) and Roy & Mandal (2021) considered the pulse-on time (T_{on}) on its own as an input parameter while Manjaiah et al. (2014a), Manjaiah et al. (2015), Kulkarni et al. (2018) and Farooq et al. (2020), among others, considered both T_{on} and pulse-off time (T_{off}) simultaneously. While some researchers such as Chaudhari et al, (2021) and Majumder & Maity (2018) considered current as an input parameter, others like Manjaiah et al. (2014a), Kulkarni et al. (2018), Farooq et al. (2020), and Sharma et al. (2021b) considered the servo voltage (SV) instead. Yunus & Alsoufi (2021) considered both voltage and current. Wire Feed (WF) is another prominent input parameter recognized by Majumder & Maity (2018), Farooq et al. (2020), Kulkarni et al. (2018), and Takale & Chougule (2019), as well as the wire/cutting speed, studied by Manjaiah et al. (2014b), Roy & Mandal (2021) (who specifically dealt with spindle rotational speed), and Sharma et al. (2021). Majumder & Maity (2018) and Manjaiah et al. (2014a) included the flushing pressure (FP) as one of the parameters to be studied. Another uncommon parameter is the type of wire used, which was considered by Manjaiah et al. (2015) and Sharma et al. (2021a). However, the most uncommon parameter considered would be wire tension, which Majumder & Maity (2018) studied in their research.

Output Parameters

The seemingly commonest output parameter taken into account for optimization across studies is the material removal rate (MRR). Chaudhari et al. (2021), Kulkarni et al. (2018) and Roy & Mandal (2021), among others, considered MRR as a factor whose maximization could affect the overall results of the machining, although the latter worked with volumetric material removal. Another common parameter across the board is the surface roughness (SR), as researched by Manjaiah et al. (2014a), Manjaiah et al. (2015), Chaudhari et al. (2020) as well as Takale & Chougule (2019). In all cases, the objective was to minimize the SR, as this is an undesirable quality to have a large value. The surface roughness could be either roughness average (Ra) or the difference between the highest peak and the lowest depth in the roughness profile (Rz). Chaudhari et al. (2021), Sharma et al. (2021a), and Sharma et al. (2021b) minimized Recast Layer Thickness (RLT). Manjaiah et al. (2015), Takale & Chougule. (2019), Sharma et al. (2021b) maximized surface topography and metallographic changes.

Sharma et al. (2021), Farooq et al. (2020) maximized profile accuracy; Majumder & Maity (2018), Chaudhari et al. (2019) and Takale & Chougule (2019) minimized micro-hardness (MH) in their studies. The least common output parameters observable are machining speed (MS), as maximized by Roy et al. (2020); morphology, as maximized by Sharma et al. (2021); hardness alteration, minimized by Sharma et al. (2021b), geometric deviation, minimized by Farooq et al. (2020); residual stresses and shape recovery ability, minimized and maximized respectively by Takale & Chougule (2019); and tool wear rate (TWR), minimized by Kulkarni et al. (2020).

5. METHOD OF ANALYSIS

The method specified the route followed to achieve the stated results in the nitinol-based study. Thus, in this section, the various methods deployed by researchers to achieve the stated results are discussed. The first step in the analysis conducted by many researchers is the Design of Experiments (DOE). There is a variety of methods through which one can do this. Roy et al. (2020) utilized the Box-Behnken Design, Farooq et al. (2020) and Manjaiah et al. (2014a) used the L27 Orthogonal array. Taguchi's utility and quality loss function was preferred by Kulkarni et al. (2018) while Farooq et al. (2020), and Manjaiah et al. (2014) used the

Signal to Noise (S/N) ratio. For the optimization process, one could follow either a single objective or multi-objective approach. The single objective approach is aimed at optimizing one output parameter at a time, while the multi-objective approach optimizes multiple parameters simultaneously. The Response Surface Methodology (RSM) adopted by Roy et al. (2020), Chaudhari et al. (2019), and Roy & Mandal (2021) was used for single-objective optimization, and the Teaching Learning Based Optimization (TLBO) Algorithm, which is a multi-objective optimization method, was followed by Chaudhari et al. (2021) and Sharma et al. (2021a). Another method that can be used is the Desirability Approach, as shown by Roy et al. (2020), which is also a multi-objective optimization method. Kulkarni et al. (2020) went with the Modified Differential Evolution (MDE) optimization technique for multi-objective optimization, Chaudhari et al. (2019) used the Heat Transfer Search (HTS) algorithm, while Yunus & Alsoufi (2021) used the Particle Swarm Optimization (PSO) method. However, Majumder & Maity (2018) combined the Multi-Criteria Decision Making (MCDM) approach, the General Regression Neural Network (GRNN) model, the Grid Search method, and Fuzzy Logic, and Multi-Objective Optimization based on Ratio Analysis (MOORA), in carrying out optimization.

To analyze the results, a noticeable favourite among researchers was the Analysis of Mean (ANOM) which was used by Kulkarni et al. (2018), Manjaiah et al. (2014a) and the Analysis of Variance (ANOVA), used by Majumder & Maity (2018), Farooq et al. (2020), Kulkarni et al. (2018), Manjaiah et al. (2015) and Manjaiah et al. (2014). Finally, for validation of results and comparison, a popular choice is the use of the Field Emission Scanning Electron Microscope (FESEM) chosen by Chaudhari et al. (2021), Majumder & Maity (2018), Roy et al. (2020), Roy & Mandal (2021). Roy et al. (2020) used the Monte-Carlo Simulation along with FESEM. Chaudhari et al. (2020), and Kulkarni et al. (2020) went with SEM along with a unique choice of Energy Dispersive X-Ray (EDX). To confirm that the shape memory effect was retained after the WEDM process, Chaudhari et al. (2019) performed a Differential Scanning Calorimetry (DSC) test.

6. OBSERVATIONS/RESULTS

After the deployment of methods to solve problems, the outputs achieved are the results. These are discussed in the present section and certain attributes of the results are also mentioned as observations. Roy et al. (2020) discovered that the highest machining speed was 2.6218mm/min and the minimum roughness average (Ra) was 1.6563µm for single-objective optimization, and for multi-objective optimization, the highest machining speed was 2.1007mm/min and the minimum roughness average (Ra) was 1.7072µm. In summarizing the result of the study, Sharma et al. (2021a) stated that the average roughness (Ra) was 0.65µm, with a profile accuracy within ±5µm; minimum hardness alteration of 34.87Hv and the RLT was less than 5µm with B-150 Nickel-Aluminum-Bronze wire. Also working on wire material type, Manjaiah et al. (2015) found that zinc-coated brass wire produced machined parts with a reduced SR and higher MRR, as well as reduced surface defects. They believe that parameters like SV, T_{on} and T_{off} have the most influence on MRR and SR, which is an opinion shared by Kulkarni et al. (2020). The experiment carried out by Kulkarni et al. (2018) informed the conclusion that pulse-on (T_{on}) time of 115µsec, pulse-off (T_{off}) time of 25µsec, wire feed of 6m/min, and spark gap set voltage of 40V supplied maximum MRR and minimal SR. They also observed that the parameter that had the most influence on the SR and MRR is the wire feed. Additionally, Manjaiah et al. (2014a) confirmed that pulse duration substantially influences MRR and SR, and large pulse duration led to surface defects like high RLT, discharged craters, and micro cracks. Finally, Farooq et al. (2020) were able to calculate a 0.250% overcut deviation in convex and a 0.236% undercut deviation in concave shapes from the desired geometric profile, with corner radii of 0.106 mm. Chaudhari et al. (2020), observed that the SR was a function of the discharge energy, which is a function of dielectric fluid pressure (flushing pressure), these all being directly proportional to one another. A similar discovery to this what that the SR was highest in areas with the most exposure to the dielectric fluid, as observed by Chaudhari et al. (2020).

7. PROBLEMS/ISSUES UNACCOUNTED FOR AND SOLUTIONS PROPOSED TO PROBLEMS

While solving problems on the nitinol based WEDM, solutions are often provided. These are discussed in the present study. After experimenting, Sharma et al. (2021b) observed that when flushing was not done properly after discharge pulses of high electrical energy, there was a substantial amount of micro-holes, melted alloy droplets, and a crater on the surfaces that had been cut using WEDM. A most commendable recommendation offered by Farooq et al. (2020) was that to reduce geometric deviations from the intended geometry of a machined workpiece, a wire offset could be introduced, along with optimized parameters, within a range of 0.169mm – 0.173mm. Likewise, Takale & Chougule, (2019) noted that recovery of the shaper memory effect of the material after WEDM could be achieved through heat treatments like annealing. Chaudhari et al. (2020) suggested that the same flushing pressure should be used on both sides of a workpiece, to ensure uniform SR on opposite sides of the workpiece.

Now, the issues not accounted for in the literature are treated here, which is mainly the real research gap promoted. The issue is to integrate the Grey Wolf Optimizer with either Taguchi-Pareto or Taguchi-ABC methods as Taguchi-Pareto Grey Wolf Optimizer or Taguchi–ABC grey wolf optimization. The article discussions on the wire electric discharge machining have developed some optimization perspectives to explain the foundation. The foundation for local and global optimization of processed materials. But treatments of Taguchi methods have only paid tangential attention to the hybridization of the Taguchi method with other methods such as Pareto analysis and the ABC analysis. Only recently in Odusoro et al (2021) was any substantial attempt made to address this problem with the hybridization of the Taguchi method with the Pareto scheme and the ABC analysis. Also interesting is the focus of the work on nitinol material, which coincides with the present study's objective. Yet, the aspect of grey-wolf optimization has been ignored in that literature source and other relevant sources. Thus, in this article, a brief on the Taguchi Pareto and the Taguchi-ABC method follows. Then some insights on the Grey Wolf Optimizer are given to motivate future studies on the subject.

The Taguchi-Pareto method is a tool to understand and implement a robust optimization scheme in surface integrity analysis. It is founded on the theories of Taguchi that examine and captures variations occurring in the process before optimizing it to achieve the average target values for the surface integrity measure (output) of the machined nitinol material. The theory of Pareto that is discriminatory by allowing only the most important part of the problem to be represented in the solution based on the 80-20 rule is the complimentary theory that makes up the Taguchi-Pareto method. The Taguchi-Pareto method assists researchers and practitioners to expand their insight on what important elements of the experimental trials represent the biggest problems that should be focused on instead of spreading energy across all the issues. The Taguchi-Pareto method has the main intent of directing the limited machining resources to the parameters that control the process most thus ensuring fairness in the distribution of resources and efficiency. Thus, the principles of cost reduction and good quality control practices of the Taguchi method with the 80-20% rule of Pareto that discriminates experimental trials makes the Taguchi-Pareto method extremely relevant to the research on surface integrity analysis because it is known when resources have prudently managed an increase in productivity of materials and profitability enhancement for the process is likely. Moreover, sustainable fabrication services demand lean practices of which one of its main pillars is resource utilization efficiency.

Thus in this context, the Taguchi-Pareto method is defined as an approach to optimization that reduces variations while concurrently prioritizing the experimental trials to yield a robust optimization framework. However, based on this definition, the Taguchi-Pareto method is structured along with the following linkages-factor-level definition, orthogonal array specification, establishment of the signal-to-noise ratio, and discrimination of the experimental trials to remove less relevant trivial few experimental trials, the definition of the optimal parametric setting and ranks of factors. On a comparative basis, the Taguchi-Pareto method is a new tool used in Taguchi optimization concerned and prioritization of experimental trials for the concentration of selection effort to the best parameters and prudently utilizing the available resources based on the 80-20pareto rule. The supporting function of the Taguchi-Pareto method in engineering is under-researched in the surface integrity analysis literature despite its first mention in composite engineering development in Ajibade et al. (2019) and its transferred knowledge to maintenance in studies involving Okanminiwei and Oke (2020) and Oji and Oke (2020). In these instances, the Pareto 80-20 rule had been incorporated with the Taguchi optimisation to assist container ports to enhance equipment handling performance and downtime (Okanminiwei and Oke, 2020) and has helped Oji and Oke (2020) to implement downtime improvement changes in the bottling plant and then promoted competitive market advantage in the plant through improved product delivery time from downtime optimization.

However, the Taguchi-ABC method is an approach to engineering optimization that concurrently optimizes and prioritizes process parameters through the Taguchi methodical route and final classification of the experimental trials into the A, B and C classifications. In the Taguchi-ABC method, the group A experimental trials are the most important followed by group B experimental trials and lastly the group C experimental trials.

The development of the Taguchi-ABC methodical literature seems to be closely associated with that of the Taguchi-Pareto method since in most cases observed the same authors tend to adopt the Taguchi-ABC method and compare it with the Taguchi-Pareto method using the same data. The contributions of Okanminiwei and Oke (2020) are examples to demonstrate this assertion in container handling systems and bottling plants, respectively. After an ABC classification scheme is unlamented, cycle counts are installed to ascertain that the surface integrity check parameters exhibit class A items as having high-priority elements. Thus, the advantages of introducing the Taguchi-ABC method in surface integrity analysis include the following. Fewer surface integrity parameters are concentrated on, second, the manufacturing resource, including labour hours are focused on parameters that improve quality substantially. Third, more closely management of surface integrity is made. Then based on the separation of less important parameters as B and C classes, an automated scheme to manage the less important B and C classes could be initiated.

Besides, some researchers innovatively combine the Taguchi method with the ABC classification concept to propose the Taguchi-ABC method. These studies have revealed that the Taguchi-ABC method may be more effective than the Taguchi method in streamlining the focus of efforts or resource distribution to the big problems, which are few controlling the system effectiveness thus causing efficiency in the utilization of resources on the most important parameters within the system. The unfair distribution of resources to the operating parameter of the surface integrity operation in the electrical discharge machining of nitinol-based material also creates friction between the operators at the work centres who may have to share resources such as energy and labour hours. It is proposed that a method of optimizations to concurrently optimize the parameters of nitinol material in surface integrity analysis and also priorities the parameters should be of great significance. This proposed method, which may be united with the Grey Wolf Optimizer can guarantee sustainable practices in the surface integrity preservation of nitinol-based machined materials as components.

In this view, some insights on the grey-wolf optimization are given as follows. With an acronym of GWO, grey wolf optimization recently emerged as a novel materialistic procedure that mimics the natural attributes of grey wolves. The animals are known to converse using body language that involves postural changes and movements. (i.e. gestures, facial expressions, touch and eye movements). They also engage in backing and scent marking among other communication patterns.

Interestingly, grey wolves exist in packs numbering between four and nine and sometimes but rarely could extend to a group between fifteen and thirty wolves. The hunting and living patterns of the grey wolves have motivated the development of the GWO. These animals can hunt within a territory between roughly 129 square kilometres and 2590 square kilometres while travelling between 8 and 64 kilometres per hour.

From the above discussion of the modified Taguchi methods and the Grey Wolf Optimizers, it is thought that merging these two methods may be innovative and potentially produces a robust solution to the production of nitinol shape memory alloys. Furthermore, some other interesting discussions are as follows. First, a researcher may enquire why the Grey Wolf Optimizer is suggested over other metaheuristics. It is acknowledged that the broad group of metaheuristics include the Grey Wolf Optimizer, ant colony optimization, simulation annealing, genetic algorithm and tabs search among others. These metaheuristics are high-echelon schemes intended to search, produce and choose a procedure that exhibits an adequately superior solution to the formulated optimization problem. However, despite the utility of these other metaheuristics, the Grey Wolf Optimizer exhibits a straightforward implementation process. Because of its simplified framework, computational needs, fewer storage requirements and faster convergence. More importantly, the GWO is preferred to other metaheuristics because it evades local minimal. Thus, from these enumerated benefits of the GWO, it is a promising tool to be chosen in future optimization research either to be used independently or in joint working with other methods.

8. CONCLUSION

The drive for the improved nitinol-based component has motivated a strong interest in surface integrity studies. Thus, in this article, a brief review of the literature regarding the surface integrity analysis of nitinol-based processed materials is conducted from 2014 to 2021. While it was found that the research gap concerning the optimization of process parameters is sparsely studied, the main gap is the absence of studies that integrate Taguchi-Pareto, Taguchi-ABC and the Grey Wolf Optimizer. Future research should address the stated issue but also could extend to other areas as follows. In the use of Taguchi methods to optimize the surface integrity of WEDM process parameters as for nitinol, the economic aspect is an important consideration that may make a huge contribution to this domain of research. Thus a further integration of the inflationary factors and interest rate into the suggested framework terminating by the desirability function as a combined Taguchi-Pareto-Grey Wolf Optimiser-desirability function inflation factor/interest rate method may be a good future pursuit. Besides this integrated study, a detailed sensitivity analysis of the method's parameters could be pursued as a future study.

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