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RESEARCH ARTICLE

Optimal Leg Linkage Design for Horizontal Propel of a Walking Robot Using Non-Dominated Sorting Genetic Algorithm

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ABSTRACT In the ever-evolving domain of robotic locomotion, leg linkage design emerges not just as an intricate engineering puzzle, but also as a decisive element in realizing optimal horizontal propulsion. The research meticulously interrogates this pivotal concern, endeavoring to harmonize multiple design objectives that traditionally exist in tension. Leveraging the robust computational prowess of the Non-dominated Sorting Genetic Algorithm (NSGA) for multiobjective optimization, this study orchestrates a deliberate foray into the expansive and complex design space. The overarching aim is not merely to pinpoint a singular, universal design zenith, but to painstakingly chart a continuum of Pareto-optimal solutions, thereby accommodating the myriad, often contradictory, imperatives that animate robotic design—from the quest for energy efficiency to the pursuit of agility, speed, and robust structural integrity. This methodology yields a rich tapestry of insights: notable among them is the discernible predilection of specific linkage configurations towards distinct performance outcomes. While certain geometries resonate more profoundly with rapid, fluid motion, others evince a marked inclination towards stability or frugal energy consumption. By dissecting these intricate relationships, and presenting them within a structured framework, this study contributes profoundly to the literature, offering both theoretical depth and pragmatic design templates to the robotics community. This synergistic marriage of computational algorithms with nuanced design challenges holds the promise to significantly recalibrate and enhance contemporary paradigms in leg linkage design for horizontally propelling robots. This study marks a significant advancement in robotic locomotion by employing the Non-dominated Sorting Genetic Algorithm (NSGA) for the first time in the optimization of leg linkage design for walking robots, providing a more nuanced understanding of the balance between structural integrity, energy efficiency, and propulsion agility. Our research elucidates a spectrum of Pareto-optimal solutions, a novel approach that offers a comprehensive understanding of the trade-offs involved in leg linkage design. Specifically, the optimized designs achieved an improvement in propulsion efficiency by reducing the approximation error to less than 0.006, and enhancing force transmission angles to over

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25 degrees. These experimental results validate the practical applicability of these designs, demonstrating a balance of improved efficiency and stability, thereby setting a new benchmark for leg linkage design in walking robots. The findings underscore the potential of NSGA in robotic design, offering a robust framework for future advancements in the field.

INDEX TERMS Walking robot, multiobjective optimization, genetic algorithm, evolutionary algorithm, NSGA, non-dominated sorting.

I. INTRODUCTION

The quest to replicate natural locomotion in robotics, particularly the nuanced dynamics of walking, stands as a formidable challenge in the field of artificial intelligence and robotics. This endeavor, aimed at emulating the diverse and intricate choreography of movement observed in the natural world, from insects to humans, encapsulates a multitude of engineering and computational complexities [1]. At the heart of this challenge is the design of leg linkages, a critical aspect that enables efficient, stable, and adaptable movement across varied terrains. The sophistication and optimization of leg linkage in walking robots are more crucial than ever, as robotics extend their reach into various sectors such as healthcare, disaster recovery, and space exploration [2].

The global market for robotics in healthcare alone is expected to reach USD 11.3 billion by 2025, growing at a CAGR of 21.6% from 2020, emphasizing the burgeoning need for advanced robotic systems [3]. Similarly, the application of robots in disaster recovery operations has witnessed a surge, with a projected increase of 15% in deployment in challenging environments by 2025 [4]. These statistics not only highlight the expanding scope of robotics but also underscore the pressing demand for innovative leg linkage designs that can adapt to diverse and often unpredictable environments.

Contrary to the seemingly effortless act of walking exhibited by living organisms, the synthetic replication of this motion presents a labyrinth of engineering challenges. Effective horizontal propulsion, a crucial element in robotic locomotion, necessitates meticulously crafted leg designs and their interconnectedness. However, achieving propulsion efficiency is just the tip of the iceberg. Robots, especially those purposed for real-world applications, are required to ensure stability, adaptability to various surfaces, energy efficiency, and quick responsiveness to environmental stimuli. A staggering 70% of robotics failures in uneven terrain are attributed to inadequate leg linkage designs, highlighting a critical area for improvement [5].

Historically, the development of leg linkages in robotics has predominantly been empirical, based on iterative prototyping and observational insights [6]. While this approach has yielded significant insights, it often lacks the precision, scalability, and efficiency required for complex robotic applications. The emergence of algorithmic optimization marks a pivotal shift in this landscape, offering a more structured and precise approach to designing leg linkages. Among various algorithms, the Non-dominated Sorting Genetic Algorithm (NSGA) emerges as a prominent solution, offering a robust framework for navigating the multifaceted challenges in multiobjective problems [7]. Rooted in the principles of evolutionary genetics, NSGA enables a systematic exploration and optimization of the convoluted design space associated with leg linkages in robotics.

The current research aims to intertwine the threads of mechanical design, robotic locomotion, and optimization. While various aspects of leg linkage design have been individually explored in the literature, a comprehensive approach that simultaneously addresses speed, stability, energy consumption, and agility is notably lacking [8]. The NSGA presents an opportunity to address this gap, providing a structured methodology to explore a spectrum of optimal leg linkage designs that cater to varied and often competing objectives.

This paper will guide readers through the intricacies of leg linkage mechanics, the underpinnings of NSGA, and their intersection in the pursuit of optimal robotic design. The approach combines theoretical modeling, simulation-driven insights, and empirical validation, aiming to contribute significantly to the discourse on robotic locomotion. The research presented herein not only seeks to address a critical technological challenge but also to deepen our appreciation of natural locomotion and the efforts to replicate it artificially [9].

In doing so, the study aims to provide a blueprint for future research and practical applications in the realm of walking robots. It is poised to make significant contributions in addressing the current limitations in leg linkage design, thereby enhancing the capabilities and performance of walking robots in various applications [10]. This endeavor is reflective of the broader aspiration within robotics and artificial intelligence - to create machines that not only mimic but also enhance human and animalistic capabilities in navigating and interacting with the physical world.

The study's findings, particularly in optimizing leg linkage design using advanced algorithms, have direct implications for real-world applications. In healthcare, this could lead to the development of more agile and efficient prosthetics or assistive robots, enhancing patient mobility. In disaster relief, robots equipped with optimized leg linkages can navigate challenging terrains more effectively, aiding in search and rescue operations. Additionally, these advancements could be pivotal in terraforming projects on extraterrestrial surfaces, where robots must adapt to unfamiliar and rugged landscapes. These practical applications underscore the study's relevance across various critical sectors.

II. RELATED WORKS

The realm of robotic locomotion, particularly in the context of walking robots, has evolved into a dynamic and multifaceted area of research, intertwining advanced approaches with mechanical design. This literature review seeks to illuminate the diverse array of studies, methodologies, and findings that have collectively shaped the current understanding and future trajectory of this field.

A. EARLY DEVELOPMENTS AND MIMETIC APPROACHES

The genesis of leg linkage design in robotics can be traced back to the early endeavors that sought inspiration from the natural world. Pioneering researchers embarked on a quest to replicate the biomechanical attributes of animals, aiming to harness the efficiency and adaptability observed in natural locomotion. Hongbin et al. provided a comprehensive overview of these early mimetic approaches, illustrating how initial robotic models endeavored to emulate the movement patterns of various creatures [11]. This biomimetic perspective was foundational in bridging the gap between biological understanding and robotic engineering.

However, the transition from biological inspiration to robotic implementation presented significant challenges. Manoonpong et al. critiqued these early mimetic models, noting that while they offered valuable conceptual insights, they frequently fell short in practical application, particularly in terms of performance and adaptability [12]. Similarly, research by Jensen and Patel [13] highlighted the complexities involved in accurately translating biological principles into mechanical designs, emphasizing the need for a more nuanced understanding of biomechanics.

These challenges led to a gradual shift in focus. As articulated by Gu et al., there was a growing recognition of the need for customized robotic design methodologies that went beyond mere imitation of natural systems [14]. This evolution was marked by an increased emphasis on developing robust and flexible design strategies, tailored specifically to meet the unique demands and constraints of robotic applications, as discussed by Macenski et al. in their exploration of adaptive robotic systems [15].

The journey from mimetic to more sophisticated robotic design approaches underscores a critical phase in the evolution of robotics, reflecting a maturation of the field as it moved from replicating nature to innovating based on biological principles.

B. ALGORITHMIC EVOLUTION AND OPTIMIZATION TECHNIQUES

The integration of algorithmic tools has revolutionized the field of robotic design, marking a significant shift from traditional design methodologies. This paradigm shift is epitomized by the work of Wang et al., who explored the application of swarm optimization techniques. Their research demonstrated how these techniques could enhance the design and functionality of multi-legged robots, setting a precedent for the utilization of advanced processes in robotic design [16].

The emergence of genetic algorithms (GAs) represents another critical milestone in robotic design optimization. Periaux and Tuovinen delved into the application of GAs for kinematic chain optimization, revealing their effectiveness in addressing complex design challenges in robotics [17]. This study highlighted the adaptability and efficiency of GAs in exploring and optimizing intricate robotic design spaces.

Further extending the scope of optimization in robotics, Bhandari et al. investigated the use of evolutionary algorithms for dynamic adaptation in robotic systems, emphasizing their role in achieving real-time responsiveness [18]. Similarly, the research by Hippalgaonkar et al. focused on the integration of machine learning methods to predict and optimize robotic behavior under varying operational conditions, illustrating the growing complexity and sophistication of algorithmic approaches in robotics [19].

The collective insights from these studies underscore the transformative impact of algorithmic tools in robotic design. They not only facilitate more effective and efficient optimization but also open avenues for innovation in addressing the multifaceted challenges of robotic systems [20]. This trend towards optimization is expected to continue, shaping the future of robotic design and functionality.

C. NON-DOMINATED SORTING GENETIC ALGORITHM (NSGA) IN LEG LINKAGE DESIGN

The NSGA and its iterations, notably NSGA-II, have revolutionized the field of multiobjective optimization. Their ability to discern and prioritize Pareto-optimal solutions has been particularly relevant for complex challenges like leg linkage design [21]. Gulec and Ertugrul demonstrated the efficacy of NSGA-II in robotic arm linkage optimization, highlighting its capacity to handle intricate design spaces and offer a spectrum of optimal solutions [22]. While their work was not directly focused on leg linkages, it provided a compelling case for the broader applicability of NSGA in robotic design.

The exploration of Non-dominated Sorting Genetic Algorithm (NSGA) in the context of leg linkage design for walking robots presents an area ripe for research, despite its established efficacy in broader multiobjective optimization tasks. Notably, the utilization of NSGA, particularly its second iteration, NSGA-II, has been limited in this domain. The pioneering work of Villarreal-Cervantes et al. stands as a significant exception, wherein NSGA-II was employed to optimize the bipedal gait of robots [23]. This study, while not directly focused on leg linkage, highlighted the algorithm's potential in enhancing robotic locomotion's efficiency and stability.

Subsequent research has sporadically tapped into the possibilities of NSGA in leg linkage design. For instance, studies by Xu et al. and later by Yu et al. have indicated the algorithm's utility in achieving optimal joint coordination, which is integral to effective leg linkage [24], [25]. More recently, the research by Zhang and Cai extended these principles to more complex multi-legged robotic systems, demonstrating NSGA-II's adaptability in diverse locomotive configurations [26]. These advancements suggest a growing recognition of NSGA's role in refining robotic movement, aligning with the current trajectory of research aimed at achieving more nuanced and efficient robotic designs [27].

The integration of NSGA in leg linkage design represents a promising frontier in robotic engineering, poised to address complex optimization challenges and propel advancements in robotic mobility and efficiency.

D. THE INTERPLAY OF OBJECTIVES IN ROBOTIC DESIGN

In the realm of robotic design, the balancing of multiple, often conflicting objectives forms a core challenge, necessitating sophisticated optimization tools. Đorđević et al. provided insights into this intricate interplay, focusing on the trade-offs between energy efficiency, speed, and stability in drone design [28]. Their exploration highlights the universal challenge in robotic engineering - optimizing one aspect often compromises another.

This phenomenon of competing objectives is not confined to drone design. Studies by Souto et al. and Zhu et al. have demonstrated similar trade-offs in terrestrial robots, where the quest for speed can adversely affect stability and energy efficiency [29], [30]. In the context of legged robots, the work of Huang et al. further elucidated these trade-offs, specifically examining how modifications in leg linkage design impact overall robot performance [31].

The criticality of addressing these conflicting requirements has led to the growing adoption of advanced optimization algorithms like the NSGA. As noted by Yuan et al., NSGA's ability to handle multiobjective problems makes it particularly suited for robotic design, where multiple performance metrics must be simultaneously optimized [32]. This shift towards algorithmic solutions underscores the evolving nature of robotic design, where the complexity of systems demands equally sophisticated optimization strategies.

E. RECENT CONTRIBUTIONS AND EMERGING TRENDS

In the ever-evolving landscape of robotic research, recent contributions have significantly broadened the scope and depth of inquiry in the field. A notable area of advancement is the integration of advanced materials and sensor technologies in leg linkage design. Pioneering this front, Lu et al. and Patrício et al. have explored innovative approaches to enhance the adaptability and responsiveness of walking robots, particularly in diverse terrains [33], [34]. Their work underscores the growing significance of material science and sensor technology in robotic design, reflecting an interdisciplinary approach that melds engineering with cutting-edge technological advancements.

Complementing these material and sensor innovations, Shi et al. ventured into the application of machine learning for predictive maintenance in robotic systems [35]. This study marks a shift towards smarter and more efficient lifecycle management of robots, addressing the often-overlooked aspect of long-term operational sustainability in robotic design. The emphasis on predictive maintenance underscores the importance of integrating advanced computational techniques to foresee and mitigate potential system failures, thereby enhancing the longevity and reliability of robotic systems.

Another emerging trend is the focus on energy-efficient designs, as highlighted in the research by Burmeister et al. and Wang et al. [36], [37]. These studies delve into the development of sustainable and energy-efficient solutions for robotic locomotion, aligning with global initiatives towards environmental sustainability. The integration of green technologies and energy-saving strategies in robotics not only addresses environmental concerns but also propels the field towards more sustainable and ecologically conscious designs.

Additionally, the exploration by Hartono et al. into the use of recyclable and biodegradable materials in robot construction reflects a growing environmental consciousness within the field [38]. Similarly, the study by Fang et al. on the application of solar energy in powering autonomous robots further emphasizes the shift towards renewable energy sources in robotic systems [39].

These recent contributions and emerging trends indicate a dynamic and multidisciplinary trajectory in robotic research, characterized by a concerted effort to address ecological concerns, enhance operational efficiency, and expand the functional capabilities of robots. As the field continues to evolve, these trends are poised to shape the future of robotic design and application.

In summary, the literature presents a rich confluence of insights, methodologies, and challenges that have collectively shaped the domain of walking robot leg linkage design. The current research, set against this backdrop, aims to bridge existing gaps and contribute to this ongoing dialogue by offering a novel integration of NSGA-driven optimization with the multifaceted challenge of leg linkage design. The future of this field appears poised for further advancements, with emerging trends indicating a move towards more sustainable, intelligent, and adaptive robotic designs. As the field continues to evolve, it will undoubtedly draw upon the diverse body of knowledge presented herein, integrating new technologies and approaches to address the ever-expanding challenges and opportunities in robotic locomotion [40], [41].

III. WALKING ROBOT LEG DESIGN BASED ON TRANSLATORY STRAIGHT-LINE GENERATOR

Designing of walking robot leg-linkage with foot center tracing along straight-line has certain advantages, considering first of all energy efficiency and simplified control [15], [22], [42], [43], [44], [45], [46], [47], [48], [49]. The prototype of horizontal propulsion mechanism designed for the legged robot is shown in Fig. 1a with foots F1 and F2 on support phase (on ground) and F3 and F4 on transfer phase (foot swing phase) [50], [51]. Using of straight-line generators for walking vehicle propel still remains a productive idea since 1878, when P. Chebyshev proposed "lambda mechanism": on Fig. 1b it is ABCD 4bar mechanism with coupler point E generating horizontal straight line when the crank AB rotates on more than 180 degrees $\phi_0 \leq \phi \leq \phi_0 + \Delta\phi$, $\Delta\phi > \pi$, where ϕ is crank rotation anlge, ϕ_0 is initial crank angle. Multi-criteria optimal design of bar linkage was carried out on previous studies applying Sobol-Statnikov method [50], [52], [53], [54], based on random search "LP-tau generator" algorithm and working with trial tables.

The main designing criteria were the best accuracy of the given output motion (straight-line trajectory of leg foot) generation (criteria c_1) and force transmission angle (criteria c_2). The additional criteria are:

criteria c_3 – crank rotation angle $\Delta\Phi$ that correspond to support phase of the leg step cycle, this criteria value has to be more than 180 degrees (in order to overlap support phases of two alternating legs [50]) and has to be maximized;

criteria c_4 – sum of the mechanism link lengths that reflects the mechanism overall dimensions and has to be minimized;

Four parameters $p_1 = r_{AB}, p_2 = l_{BC}, p_3 = l_{CD}, p_4 = \boldsymbol{\phi_0}$ are varied within the given boundaries using so called "random LP-tau sequence generator" [54], whereas 6 specific parameters $x_1, \ldots, x_6$ are determined to meet the main criteria c_1. The designing task is formulated as the following minimization problem

$$\delta = \sum_{I=1}^{n} \delta_I^2 => \min_{x_E, y_E, S_x, S_y} \tag{1}$$

where δ_i is design error – the distance between actual positions E_i and the desired ones E_i^*, i-1,..., N, of foot center E:

$$\delta^2 \equiv \left\| E_i E_i^* \right\|_2^2 \tag{2}$$

The approximation function δ was minimized in order to meet criteria c_1. With the given varied parameter $p_1, \ldots, p_4$ values, the analytical solution for the variables $x_1, \ldots, x_6$ was found as the solution of 6 linear equations [50] of the following form

$$Ax = b \tag{3}$$

with 6×6 matrix A and vector b

$$A = \begin{bmatrix} E & A_1 & A_2 \\ A_1^T & E & \frac{1}{2}E \\ A_2^T & \frac{1}{2}E & \frac{1}{N}\sum\limits_{i=1}^{N} k_i E \end{bmatrix} \tag{4}$$

$$E = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \tag{5}$$

$$A_1 = \begin{bmatrix} -\frac{1}{N}\sum\limits_{i=1}^{N} \cos\beta_i & -\frac{1}{N}\sum\limits_{i=1}^{N} \sin\beta_i \\ \frac{1}{N}\sum\limits_{i=1}^{N} k_i \sin\beta_i & -\frac{1}{N}\sum\limits_{i=1}^{N} k_i \cos\beta_i \end{bmatrix} \tag{6}$$

$$A_2 = \begin{bmatrix} -\frac{1}{N}\sum\limits_{i=1}^{N} k_i\cos\beta_i & -\frac{1}{N}\sum\limits_{i=1}^{N} k_i\sin\beta_i \\ \frac{1}{N}\sum\limits_{i=1}^{N} k_i \sin\beta_i & -\frac{1}{N}\sum\limits_{i=1}^{N} k_i \cos\beta_i \end{bmatrix} \tag{7}$$

$$\begin{aligned} b &= [b_1, b_2, \ldots, b_6]^T \\ b_1 &= -\frac{1}{N}\sum_{i=1}^{N}\left(X_{B_i}\cos\beta_i + Y_{B_i}\sin\beta_i\right) \\ b_2 &= \frac{1}{N}\sum_{i=1}^{N}\left(X_{B_i}\sin\beta_i - Y_{B_i}\cos\beta_i\right) \\ b_3 &= \frac{1}{N}\sum_{i=1}^{N} X_{B_i} \\ b_4 &= \frac{1}{N}\sum_{i=1}^{N} Y_{B_i} \\ b_5 &= \frac{1}{N}\sum_{i=1}^{N} k_i X_{B_i} \\ b_6 &= \frac{1}{N}\sum_{i=1}^{N} k_i Y_{B_i} \end{aligned} \tag{8}$$

The parameters $p_1, \ldots, p_4$ are varied by the Sobol-Statnikov random LPτ-sequence method [50], the boundaries of the search were set by the following restrictions

- $0.175 \leq p_1 \leq 0.500$,
- $0.410 \leq p_2 \leq 1.200$,
- $0.530 \leq p_3 \leq 1.200$,
- $40^0 \leq p_4 \leq 100^0$.

For each values of the parameters $p_1, \ldots, p_4$

- we determine the worst value $\mu_e = min(|\mu_i|, 180\text{-}|\mu_i|)$ of the force transmission angle μ_i, $i = 1, \ldots, N$;
- determine 6 synthesis parameters $\mathbf{X} = [x_1, \ldots, x_6]^{\mathrm{T}}$ by solving system of linear equations (9);
- determine the worst deviation from the desired trajectory (approximation error) $\varepsilon = \max\limits_{i=1..N} \sqrt{\left\| E_i E_i^* \right\|_2^2}$;

record the results in the trial Table (in Appendix II).

Table 1 presents the key notations utilized within the optimization model framework.

IV. PARAMETER OPTIMIZATION FOR HORIZONTAL PROPEL OF A WALKING ROBOT

A. PRELIMINAL RESULTS OPTIMIZING TWO CRITERIA: C_1 AND C_2

After analyzing the trial Table and removing unfavorable solutions, we conduct a feasibility study of the designed 4bar mechanism, estimate the criteria values variation range and determine the new boundaries of variable parameters

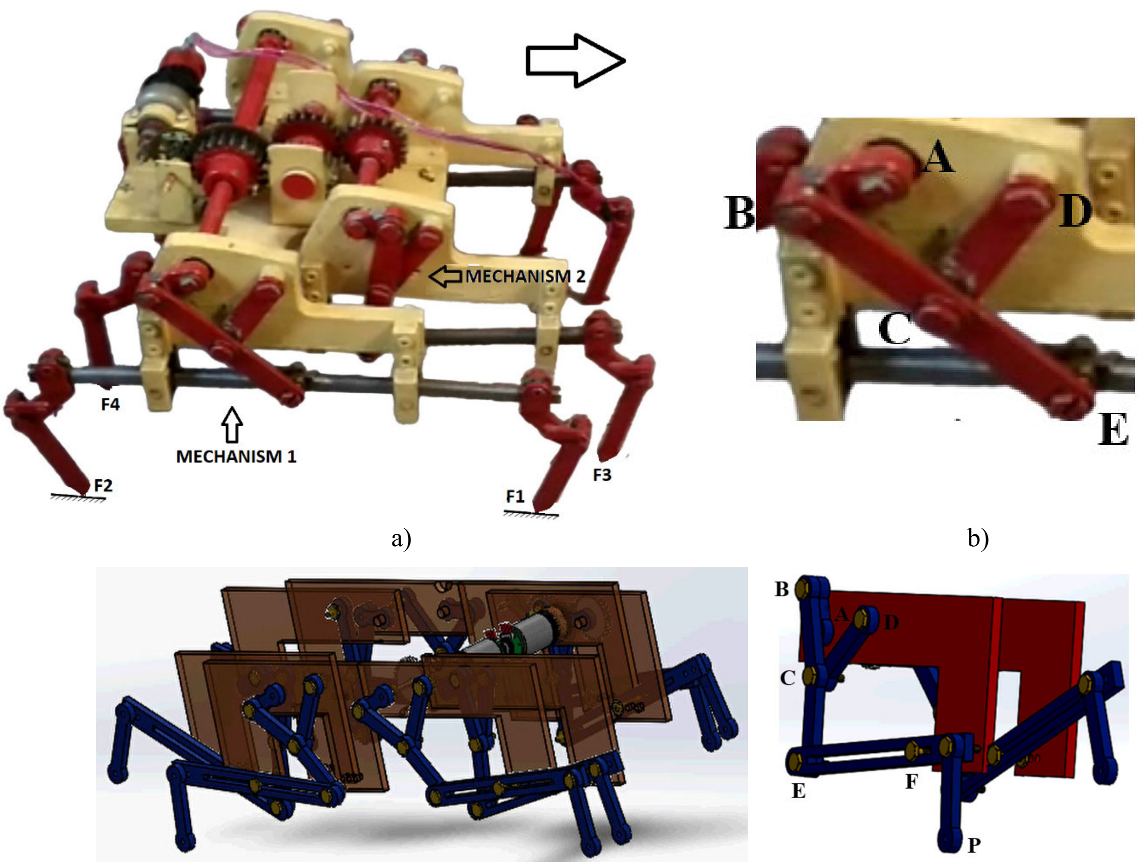


FIGURE 1. Prototype of the legged robot horizontal propulsion mechanism (a, b) and 3d-modell (c, d).

variation. After repeating these steps few times finally we finish global search within the given search area. Then we approach the final solution that meet all designing criteria and then carry out local search in the neighborhood of the chosen solution and try to improve design criteria. Initially, the parameter $\Delta\Phi$ is set to a fixed value of 220 degrees.

Table A1 "Fragments of the truncated Trial Table with the best accuracy ε (criterion c_1)" (see Appendix I) shows the truncated trial Table fragment with the best accuracy (ordered by increasing approximation error) and Table A2 "Fragments of the truncated Trial Table with the best force transmission angle μ_e(criterion c_2)" shows the trial Table fragment with the best motion transfer (ordered by decreasing force transmission angle μ_e), that were obtained as the result of global search. The variation range of the criteria c_1 and c_2 are found to be as follows: the accuracy limit $\varepsilon < 0.006$ (0.6% of the trajectory length) and the force transmission angle limit $\mu_e >$ 22 degrees.

Here, we grapple with a highly intricate and labor-intensive design process. When we attempt to enhance one of these criteria, it often leads to a deterioration in another criterion, as it is seen by analyzing the scatter of the acceptable solutions under the indicated boundaries (Fig. 2 and Fig. 3). Thus, we deal with the conflicting criteria: as the accuracy improves, the force transmission angle deteriorates and vice versa. For example, one can observe from the resulting diagrams that the best parameter values (X_D–Y_D) in terms of accuracy (red dots) lie in the lower right corner (Fig. 2a), while acceptable solutions (X_D–Y_D), corresponding to good force transmission angles, lie in the upper left corner (red dots in Fig. 3a). The best parameter values (r_{AB}–ϕ_0) in terms of accuracy lie in the upper left corner (red dots in Fig. 2b), while the best solutions (r_{AB}–ϕ_0), corresponding to good force transmission angles lie in the lower right corner (Fig. 3b). Finally, the best parameters (x_E–y_E) lie at the bottom in terms of accuracy (red dots in Fig. 2c), and shifted upward in terms of force transmission angle (red dots in Fig. 3c).

Generating the trial Tables and analyzing them, after few steps we approach to compromise solutions that satisfy the considered conflicting criteria. After working with truncated trial Tables, we further discard solutions with restrictions $\mu_e < 24$ deg. and $\varepsilon > 0.0057$, finally the compromise solutions were found: the best solutions in terms of accuracy are shown in Table A3 "Truncated Trial Table: Best Accuracy Solutions with Force transmission Angle Limitation $\mu_e >$ 23.5 deg" (Appendix I), in terms of force transmission angle - in Table A4 "Truncated Trial Table: Best Force transmission Angle Solutions with Accuracy Limit $\varepsilon < 0.0058$"

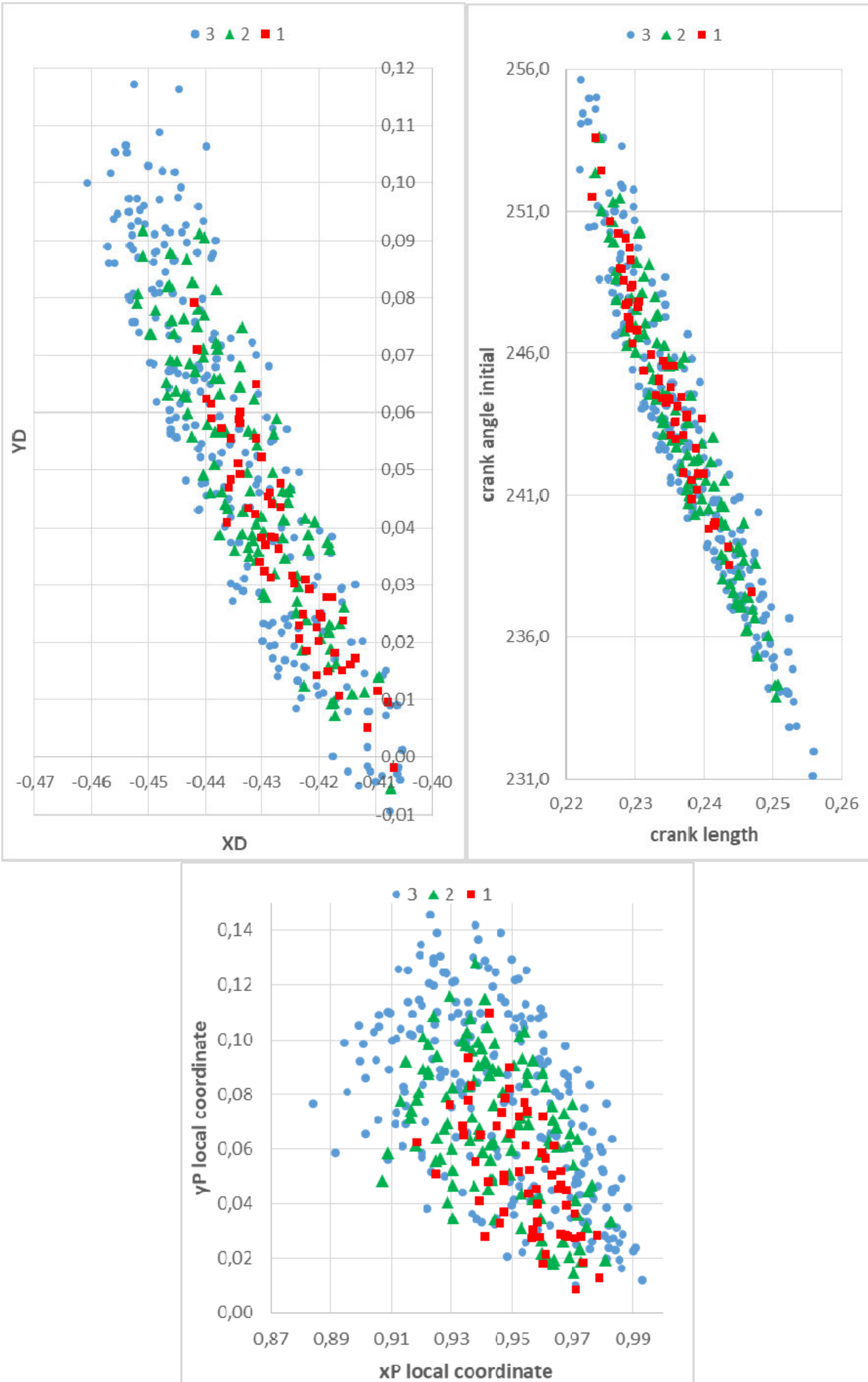


FIGURE 2. Scatter of solutions with best accuracy: "1' – $\varepsilon \leq 0{,}0054$ '2' – $0{,}0054 < \varepsilon \leq 0{,}0057$ '3' – $0{,}0057 < \varepsilon \leq 0{,}006$.

(Appendix I). As a result of the analysis of these Tables, the first line of Table A4 "Truncated Trial Table: Best Force transmission Angle Solutions with Accuracy Limit $\varepsilon < 0.0058$" with the LP_τ- sequence number 10995 was chosen as the optimal solution; best force transmission angle $\mu_e = 25.1$ deg; however, the loss in accuracy is not significant:

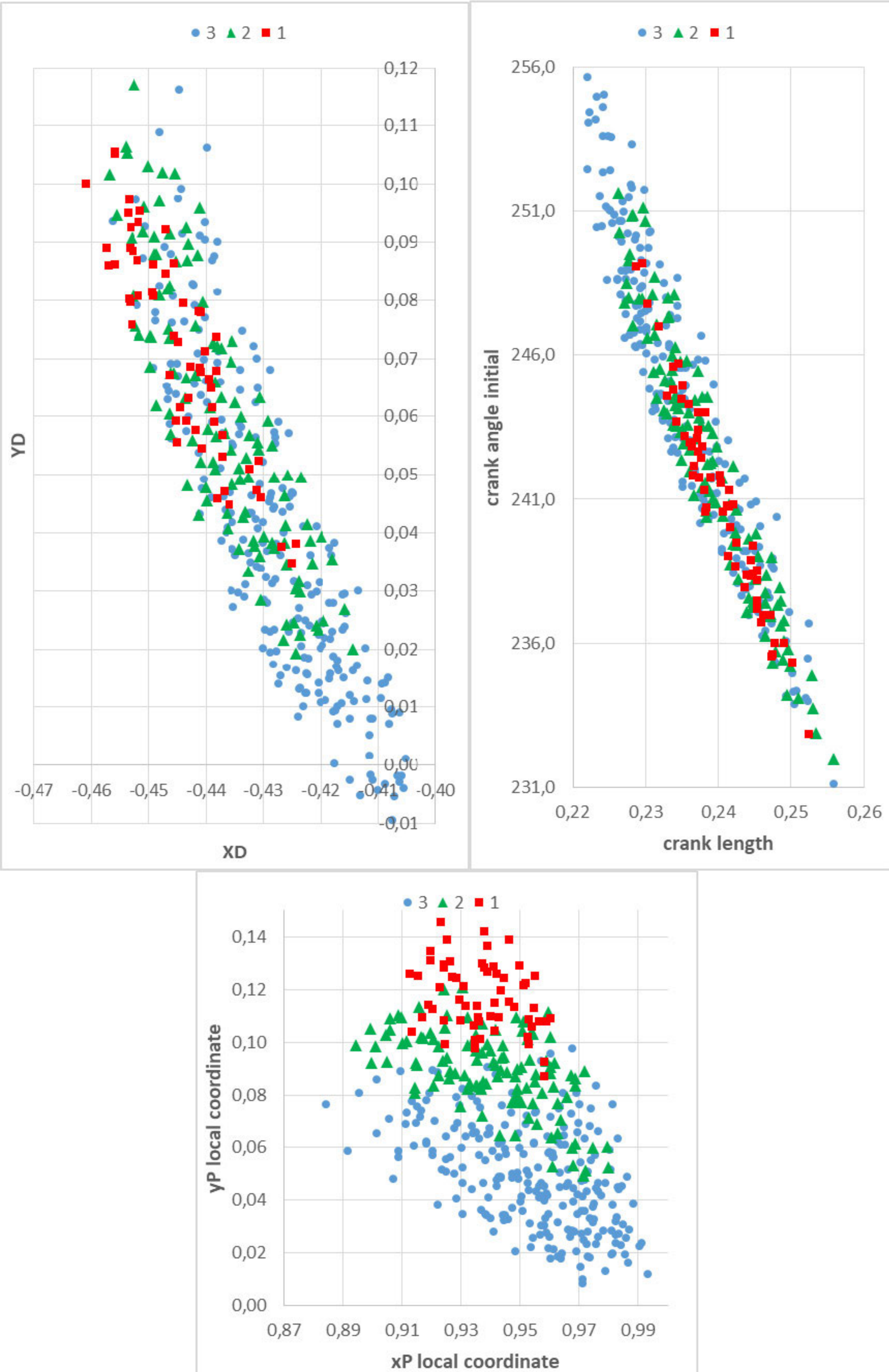


FIGURE 3. **Scatter of solutions with the best force transmission: '1' – $\mu e \geq 24$grad. '2' – 23,5$\leq \mu e <$ 24 (grad) '3' – 22$\leq \mu e <$23,5 (grad).**

TABLE 1. Main notations used in the optimization model.

Parameter	*Notation*
$c_1 = \delta = \sum_{i=1}^{N} \delta_i^2$ $c_2 = \mu_e = \min(\lvert\mu_i\rvert, 180 - \lvert\mu_i\rvert)$	Criterion 1: accuracy of the output trajectory of the leg (foot center trajectory accuracy) Criterion 2: force transmission angle
$c_3 = \Delta\Phi$	Criterion 3: crank rotation angle $\Delta\Phi$ that correspond to support phase of the leg step cycle
$c_4 = \sum\{lengths\}$	Criterion 4: sum of the mechanism link lengths that reflects the mechanism overall dimensions and has to be minimized
$p_1 = r_{AB}$	Varying parameter: crank (AB) length
$p_2 = l_{BC}$	Varying parameter: length of the link BC
$p_3 = l_{CD}$	Varying parameter: length of the link CD
$p_4 = \Phi_0$	Varying parameter: initial rotation angle of the crank AB
$x_1 = x_E$	Variable: local coordinates of E w.r.t the coordinate system Bxy, where $Bx \supset \overrightarrow{BC}$
$x_2 = y_E$	Variable: local coordinates of E w.r.t the coordinate system Bxy, where $Bx \supset \overrightarrow{BC}$
$x_3 = S_x$	Variable: absolute coordinates of $E_1^{'}$
$x_4 = S_y$	Variable: absolute coordinates of $E_1^{'}$
$x_5 = L\cos\alpha$	Variable: where L is the length of the straight-line segment of the foot trajectory, α is an inclination angle of the straight-line segment of the foot trajectory
$x_6 = L\sin\alpha$	Variable: where L is the length of the straight-line segment of the foot trajectory, α is an inclination angle of the straight-line segment of the foot trajectory

the accuracy ε =0.0057 is very close to the best accuracy ε =0.0052 obtained from Table A3 "Truncated Trial Table: Best Accuracy Solutions with Force transmission Angle Limitation $\mu_e > 23.5$ deg".

Noteworthy three more solutions within the Top 14 of both Tables A3 and A4: these are solutions with LP_τ- sequence numbers 29755, 23207 and 10823.

Analyzing the trial tables truncated by the accuracy $\delta \leq 0.006$ (0.6% from stride – step length) and force transmission angle $\mu_e \geq 22$ degrees are obtained and studied. The mechanism dimensions with the best accuracy and the best force transmission angle are in Table 2.

The final six-link mechanism is plotted in Fig. 4. The wide adaptation range to terrain irregularities is ensured due to straight-line and translational motion of the output link *EF*.

B. MULTIOBJECTIVE OPTIMIZATION

One can observe, that treating with trial Tables is very laborious task even with two designing criteria that conflict with each other and with 3 or 4 designing criteria the problem is more complicated. Striving to enhance accuracy (c1) often

TABLE 2. The mechanism dimensions with the best accuracy.

r_{AB} [m]	l_{BC} [m]	l_{CD} [m]	X_D [m]	Y_D [m]	φ_0, [deg]
0,2335	0,4926	0,5037	-0,4243	0,0301	245
$x_1 = x_E$	$x_2 = y_E$	$x_3 = S_x$	$x_4 = S_y$	δ	μ_e
0,9568	0,0271	2,0543	1,8465	0,0049	22,2

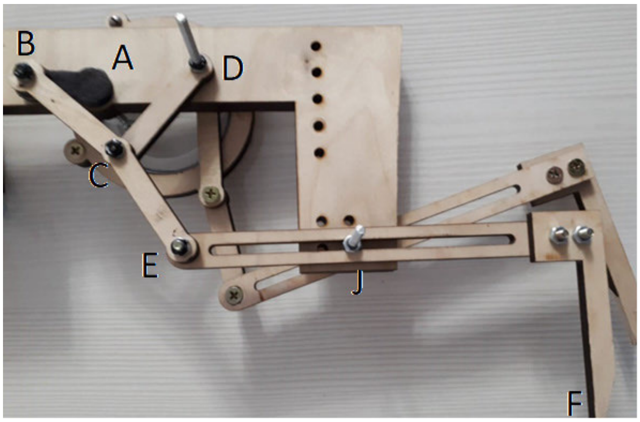


FIGURE 4. Designed leg mechanism.

results in a deterioration of force transmission criteria (c2), and vice versa. Therefore, the compromise can be achieved by yielding some of the parameters, thus we decided to give in the parameter $\Delta\Phi$. So further we varied this parameter too within the range $180 \leq \Delta\Phi \leq 220$. As fifth variable $p_5 = \Delta\Phi$. The fragment of new Trial table is shown on Table 4. Full form of Table 3 is given in Appendix I. It consists of 2384 records. Our goal is to find 100 best solutions that which lie in a Pareto optimal front. To solve this problem, we apply non-dominated sorting genetic algorithm.

C. MULTIOBJECTIVE OPTIMIZATION USING NON-DOMINATED SORTING GENETIC ALGORITHM

Multi-Objective Optimization Problems (MOOP) and Pareto Dominance are fundamental concepts in the optimization field [55]. A Multi-Objective Optimization Problem (MOOP) can be formally described as:

Given a vector function $F(x) = [f_1(x), f_2(x), \ldots, f_m(x)]$, where each $f_i(x)$ is an objective function, and a decision vector $x = [x_1, x_2, \ldots, x_n]$ from a decision space X.

The task is to find a vector that is 'optimal' according to some criterion. Mathematically, the MOOP can be stated as follows:

$$\min imize/\max imize\ F(x) = [f_1(x), f_2(x), \ldots, f_m(x)]$$
$$Subject\ to\ x \in X \tag{9}$$

For example, in a two-objective optimization problem (m = 2), we are trying to find a decision vector x that can simultaneously minimize/maximize both and $f_2(x)$.

TABLE 3. Samples of the trial table.

N	LP_τ	Y_E^0	ε (c_1)	μ_e (c_2)	$\Delta\Phi$ (c_3)	summL (c_4)
1	1657	-0,85063	0,00384	23,28323	201,55762	2,23839
2	6025	-0,90412	0,00460	26,87876	193,94409	2,45759
3	5958	-0,88176	0,00564	40,22063	190,78003	3,06220
4	474	-0,66227	0,00639	40,44764	194,62891	2,98971
5	1298	-0,69464	0,00670	46,99357	197,71973	3,38041

Pareto Dominance is one of the most commonly used criteria to define 'optimality' in a MOOP. Given two decision vectors x_1 and x_2. x_1 is said to Pareto dominate x_2 if:

1. x_1 is no worse than for all objectives. Mathematically, for all i *in* $\{1, 2, \ldots, m\}, f_i(x_1) \leq f_i(x_2)$ if we are minimizing or if we are maximizing.

2. x_1 is strictly better than in at least one objective. Mathematically, there exists a j *in* $\{1, 2, \ldots, m\}$ such that if we are minimizing or fj(x1) > fj(x2) if we are maximizing.

Mathematically, x_1 Pareto can be represented as follows [56]:

$$
\begin{aligned}
&\forall i \in \{1, \ldots, m\}, f_i(x_1) \leq f_i(x_2) \\
&or \\
&(or\ f_i(x_1) \geq f_i(x_2)\ for\ \max imization) \\
&\exists j \in \{1, \ldots, m\}, f_j(x_1) < f_j(x_2) \\
&or \\
&\left(or\ f_j(x_1) \geq f_j(x_2)\ for\ \max imization\right)
\end{aligned} \tag{10}
$$

A decision vector is considered Pareto optimal if there's no other decision vector in X that Pareto dominates it. The set of all Pareto optimal decision vectors forms the Pareto front. In graphical representations of a MOOP with two objectives, the Pareto front is typically depicted as a curve or a set of points. Moving from a point on the curve to another point not on the curve would lead to a deterioration in at least one objective. This captures the notion of trade-offs in MOOPs [57].

Pareto Dominance is a fundamental concept in multi-objective optimization, guiding the search toward solutions that balance conflicting objectives. It also serves as a criterion for comparing and selecting these solutions. Fig. 5 demonstrates example of Pareto dominance.

The Non-dominated Sorting Genetic Algorithm II (NSGA-II), introduced by K. Deb et al., has solidified its reputation as an exemplary technique for tackling multi-objective optimization problems [58]. NSGA-II, founded upon evolutionary computation principles, distinguishes itself with its capacity for efficient non-dominated sorting and a well-conceived crowding distance computation [59].

Primarily, the NSGA-II operates by generating a population of potential solutions that are then evolved over a series of iterations or generations. This evolution is guided by principles mimicking biological evolution, such as selection, crossover, and mutation [60]. Fig. 6 describes the concept of

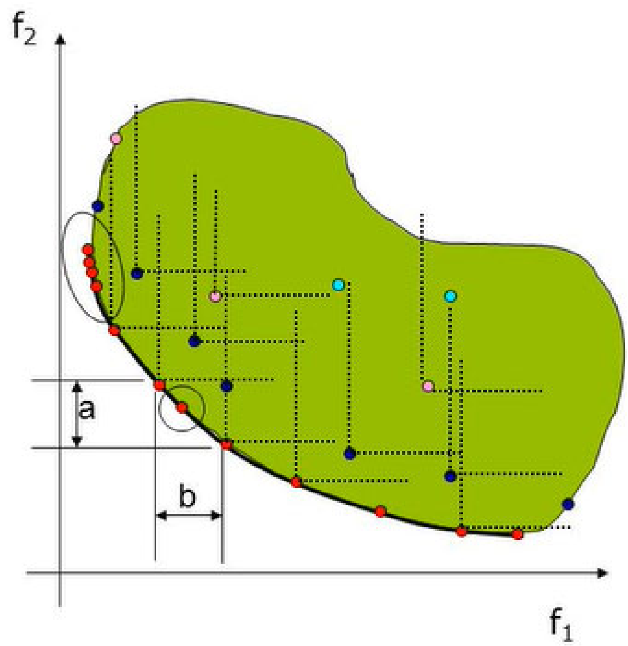


FIGURE 5. Example of Pareto dominance.

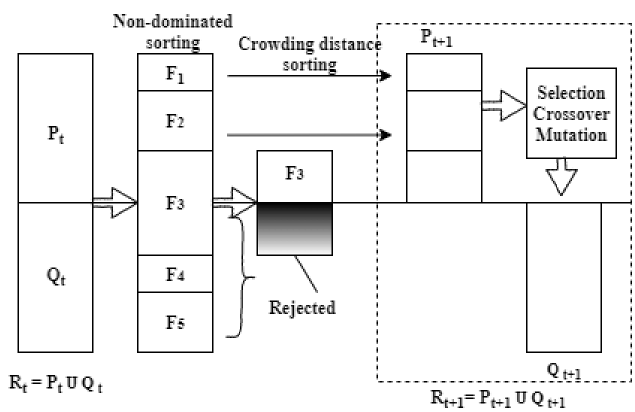


FIGURE 6. Non-dominated sorting genetic algorithm for Pareto optimal solution.

the proposed solution using non-dominated sorting genetic algorithms.

1) NON-DOMINATED SORTING

The algorithm commences with an initial population, which is randomly generated. For each subsequent generation, the algorithm first combines the current population, P_t, and the offspring population, formed from P_t, into a combined population; this combined population is of size if and are of a size N.

The combined population, R_t then undergoes non-dominated sorting. This process segregates solutions into different "fronts" based on Pareto dominance. The first front, F1, is the set of solutions in Rt that are not dominated by any other solution. The second front, F2, is the set of solutions not dominated when solutions in F1 are disregarded, and so on. As we demonstrated before, equation (2) describes the concept of Pareto dominance. Subsequently, solutions within each front are assigned a crowding distance [61].

2) CROWDING DISTANCE

The crowding distance measures the density of solutions surrounding a particular solution in the objective space [62]. It estimates the size of the giant cuboid enclosing the solution without including any other solution within the objective space. Solutions with more considerable crowding distances are considered better as they are less crowded.

3) SELECTION

Following the non-dominated sorting and crowding distance assignment, the next generation, P_{t+1}, is selected [63]. Starting from the first front, whole fronts are included in P_{t+1} until adding the next front would cause the size of Pt+1 to exceed N. The solutions in this "last" front are sorted by crowding distance, and only the solutions with the most incredible crowding distances are included until $|P_{t+1}| = N$.

4) CROSSOVER

The newly formed population, Pt+1, undergoes crossover and mutation operations to form the offspring population for the next generation, Qt+1 [64]. These operations use genetic algorithm principles to form new solutions from existing ones, aiding the exploration of the solution space.

5) MUTATION

Following crossover, the mutation is applied to the offspring [65]. Mutation introduces small random changes in the offspring, helping to maintain diversity in the population and preventing premature convergence. Like crossover, the mutation operator in NSGA-II is often a polynomial mutation suited to continuous problem domains.

Fig. 7 demonstrates the block schema of the proposed NSGA-II solution for a multiobjective optimization problem. NSGA-II finds a diverse set of Pareto-optimal solutions, capturing the trade-offs between conflicting objectives. Its non-dominated sorting approach ensures that the generated solutions are high quality, while the crowding distance ensures a good spread of solutions along the Pareto front.

Given its balance between exploration and exploitation, NSGA-II is well-suited for multi-objective optimization in multiple selection problems, where there are numerous potential solutions and multiple criteria for evaluating the quality of a solution. Its genetic algorithm basis allows it to navigate the vast solution space effectively, offering a robust and flexible approach to such problems.

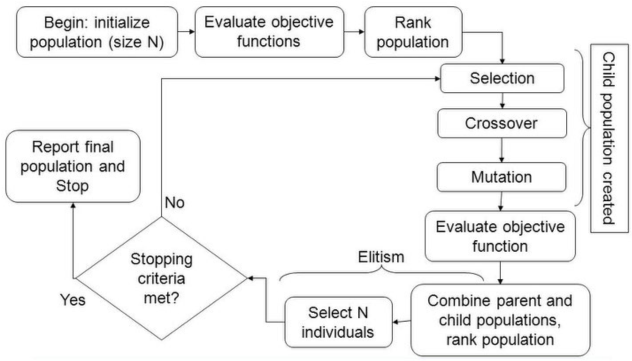


FIGURE 7. Flowchart of non-dominated sorting genetic algorithm for Pareto optimal solution.

TABLE 4. Design space.

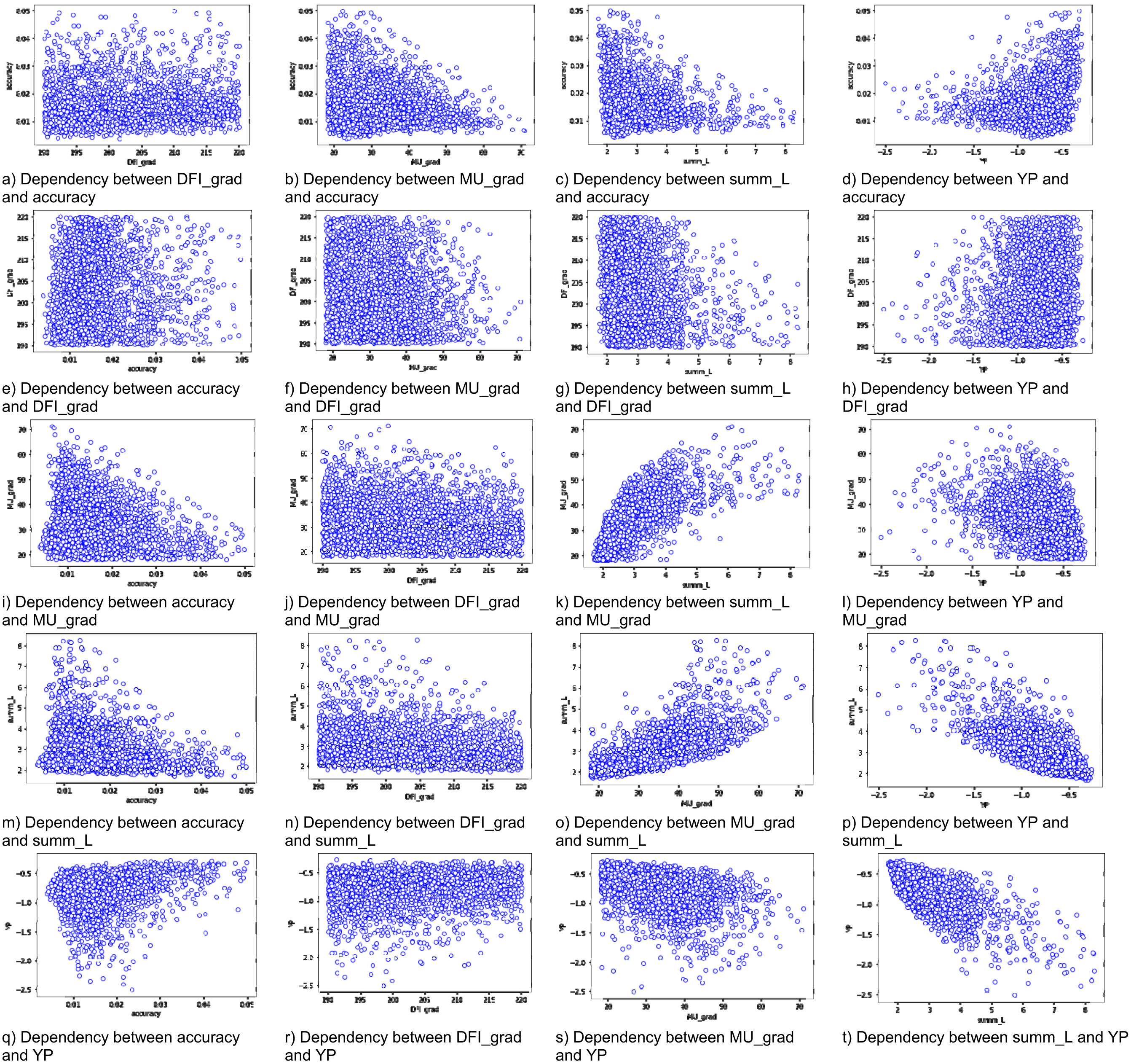
Experiment #	Population size	Simulated binary crossover	Mutation (ETA)	Generation
1	100	0.9	20	40
2	60	0.9	20	40
3	100	0.9	20	40

By orchestrating these steps in concert, NSGA-II presents a practical evolutionary approach to multi-objective optimization, effectively handling problems with multiple conflicting objectives. In the realm of Multiple Selection problems, where one needs to identify optimal subsets from a more extensive set considering multiple criteria, NSGA-II serves as a robust method to navigate the complex landscape of trade-offs and find a diverse set of high-quality solutions [8].

V. EXPERIMENT RESULTS

In the context of optimization and engineering design, the "design space" refers to all possible combinations of design variables or parameters that can be considered when solving an optimization problem. After defining the problem statement and objective functions, we started to minimize by using NSGA2 with the parameters. Table 4 demonstrates the configuration parameters of NSGA-Net for the experiment.

Figure 8 delineates the dependencies extant among a set of five distinct parameters, thereby offering a visual exploration of the intricate interrelationships and interconnectedness woven amongst them. The graphical representation enables to visually dissect the nuanced dynamics and correlations shared among the parameters, which can be indispensable in comprehending their collective behavior and potential impacts on the outcomes. Consequently, Figure 8 emerges as an essential analytical tool, serving to illuminate the nuanced, and potentially non-linear, interactions within the parameters, thereby aiding in the formulation of hypotheses and analytical models which may subsequently guide further research



a) Dependency between DFI_grad and accuracy
b) Dependency between MU_grad and accuracy
c) Dependency between summ_L and accuracy
d) Dependency between YP and accuracy
e) Dependency between accuracy and DFI_grad
f) Dependency between MU_grad and DFI_grad
g) Dependency between summ_L and DFI_grad
h) Dependency between YP and DFI_grad
i) Dependency between accuracy and MU_grad
j) Dependency between DFI_grad and MU_grad
k) Dependency between summ_L and MU_grad
l) Dependency between YP and MU_grad
m) Dependency between accuracy and summ_L
n) Dependency between DFI_grad and summ_L
o) Dependency between MU_grad and summ_L
p) Dependency between YP and summ_L
q) Dependency between accuracy and YP
r) Dependency between DFI_grad and YP
s) Dependency between MU_grad and YP
t) Dependency between summ_L and YP

FIGURE 8. Dependencies between parameters.

and investigative endeavors into the underlying mechanisms propelling these observed interdependencies.

In Fig. 9, an empirical correlation is manifested between authentic data, as procured from the sampling table, and solutions generated employing the Non-dominated Sorting Genetic Algorithm (NSGA-II) method. The red dots symbolize the genuine data, meticulously obtained utilizing the table of samples, while the blue dots represent generated solutions situated within the Pareto dominance boundary. A discernable high correlation is observed between these two data sets, signaling the efficacy and precision of the NSGA-II in approximating real-world data.

Moreover, the terminal chart contained in Figure 9 unveils the Pareto front, which has been extracted through the judicious application of the NSGA-II algorithm. This graph not only provides a visual representation of the non-dominated solutions in the objective space but also underscores the algorithm's capability to effectively navigate through the solution space, ultimately yielding an approximation of the true Pareto front. This is a crucial point, as the Pareto front embodies solutions for which no other feasible solutions are demonstrably superior when considering all objectives concurrently, thus offering valuable insight into the inherent trade-offs present among the multiple objectives under consideration.

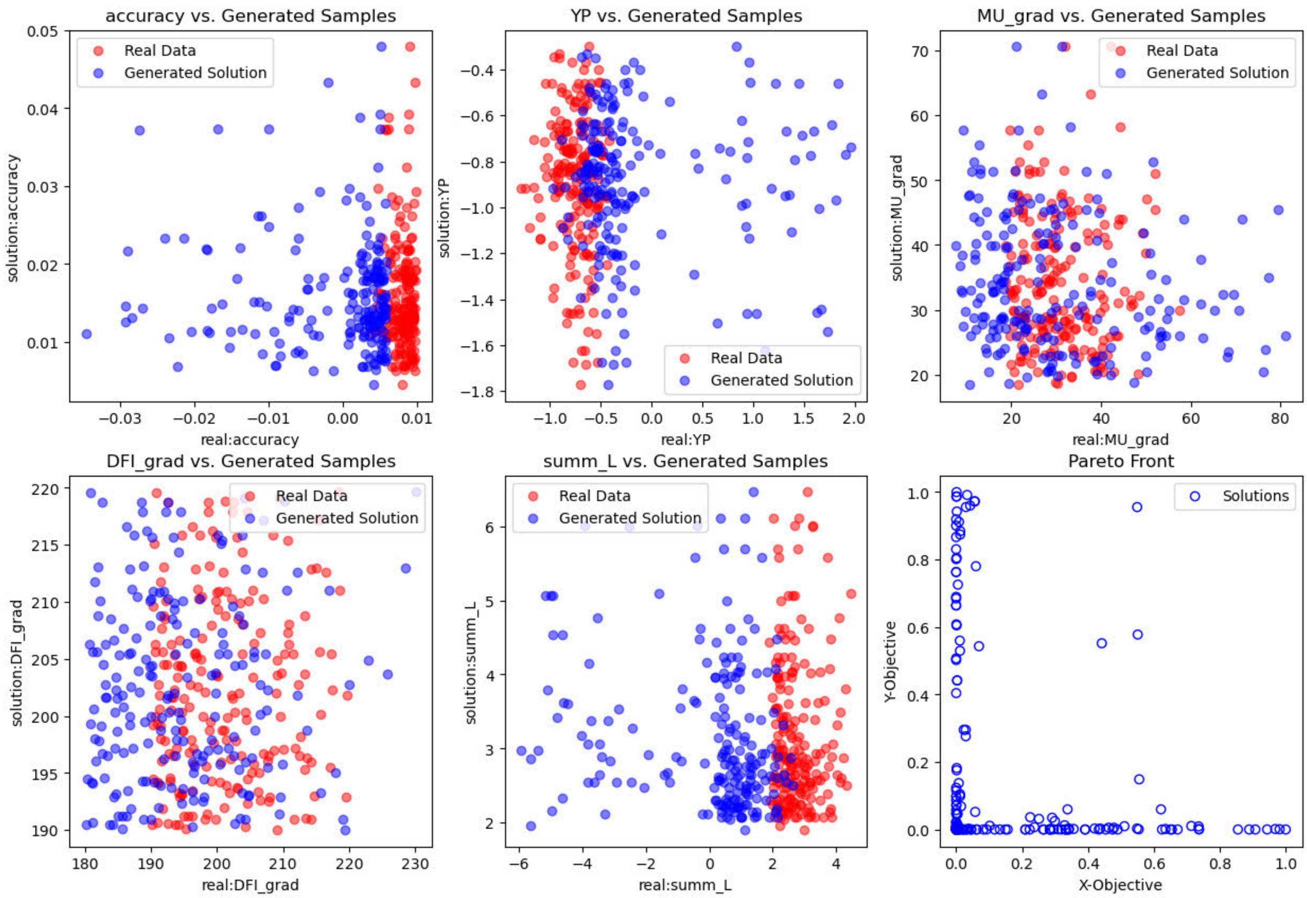


FIGURE 9. **Obtained results.**

In this manner, the depicted correlation and resultant Pareto front affirm the pragmatic utility of employing the NSGA-II method in navigating complex, multi-objective optimization landscapes, thereby facilitating informed decision-making processes predicated upon a rigorous, computational exploration of possible solutions.

Fig. 10 illustrates the convergence trajectory of the Non-dominated Sorting Genetic Algorithm (NSGA) in the multi-dimensional optimization of five parameters. The depicted results unambiguously reveal that the algorithm successfully navigates towards a convergence hypervolume of 1.0, a feat achieved approximately within 2000 iterations. In multiobjective optimization, a convergence hypervolume of 1.0 signifies that the algorithm has comprehensively covered the defined objective space, effectively approximating the true Pareto front by optimally balancing and representing all competing objectives.

It is pivotal to note that the convergence towards a hypervolume of 1.0 is indicative of an optimal Pareto front, thereby suggesting that the algorithm proficiently identifies a set of non-dominated solutions which populate the defined objective space. In this context, "non-dominated" refers to solutions for which no other feasible solutions are definitively superior when considering the multiplicity of objectives concurrently.

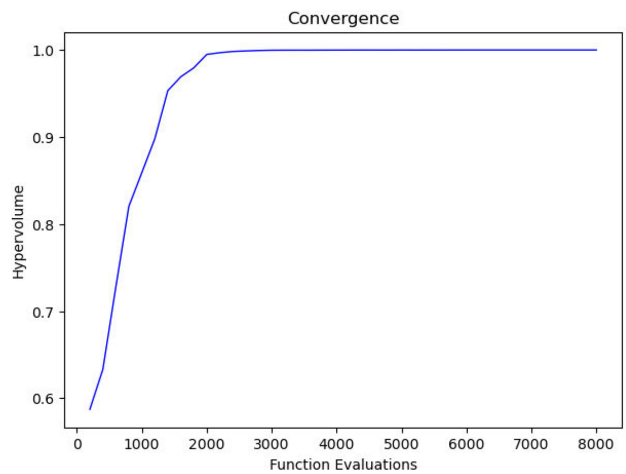


FIGURE 10. **Convergence of the applied NSGA-II algorithm.**

The convergence process, as visualized in Fig. 10, underscores the algorithm's efficacious ability to traverse the solution space and iteratively refine the solution set, successively approximating the true Pareto front with each iteration. This aptitude for systematic convergence not only underscores the algorithm's robustness in navigating the complexity inherent in multi-objective optimization tasks but also enhances its utility in facilitating discerning, informed decision-making processes predicated upon a nuanced exploration of the feasible solution space.

It is imperative to underscore that a more detailed analysis, including an examination of the algorithm's sensitivity to initial conditions, parameter tunings, and its scalability and performance relative to alternative optimization algorithms, would offer a more comprehensive understanding of its practical applicability and performance in varied problem domains.

Fig. 11 provides a systematic exposition of solutions distinctly situated on the boundary of the Pareto-optimal set, ascertained through both empirical experimentation and the application of the Non-dominated Sorting Genetic Algorithm II (NSGA-II). In this illustrative depiction, solutions discerned via the NSGA-II are delineated in a prominent blue, whereas those derived through tangible experimental endeavors are distinctly demarcated in red. A notably robust correlation between these disparate data sets tangibly underscores the high precision and reliability of the adopted methodological paradigm, demonstrating that the NSGA-II algorithm materially contributes to the derivation of solutions congruent with those obtained through practical methodologies.

It is crucial to emphasize that the NSGA-II algorithm is distinguished for its adept proficiency in accurately delineating the Pareto front within a multi-criteria optimization context. This makes it particularly poignant for comparison against practical solutions. In this context, the pronounced correlation between solutions elicited via the NSGA-II and those achieved through pragmatic means provides a compelling testament to the substantial applicability and efficacy of this algorithm within the considered optimization problem spaces. Future research could judiciously explore further the specificities and potentials of the NSGA-II algorithm across assorted application domains, comparatively assessing its performance against alternative evolutionary and metaheuristic algorithms to endow a more comprehensive understanding of its applicability and potency in multi-criteria optimization.

VI. DISCUSSION

The convergence of optimal leg linkage design and the application of the Non-dominated Sorting Genetic Algorithm (NSGA) presents an exciting intersection in the evolution of robotic locomotion. As we synthesize the findings from our study, it is evident that integrating computational optimization with practical design challenges can spur innovative solutions. This discussion, therefore, seeks to delineate the advantages that emerged from our research while simultaneously casting a gaze into the potential future directions in this dynamic field.

A. OVERVIEW OF CHOSEN NSGA METHODOLOGY

In this study, we meticulously selected an advanced iteration of the traditional Non-dominated Sorting Genetic Algorithm (NSGA) framework, a decision grounded in the algorithm's demonstrated proficiency in complex multiobjective optimization challenges. Our choice was influenced by the algorithm's ability to effectively balance competing objectives, a critical aspect in robotic leg linkage design. This advanced NSGA iteration brings enhanced efficiency and nuanced optimization capabilities, distinguishing it from its predecessors.

The rationale behind adopting this sophisticated NSGA variant was twofold. Firstly, its robustness in handling multi-faceted optimization tasks aligns seamlessly with the intricate nature of leg linkage design, where factors such as energy efficiency, structural integrity, and adaptability are in constant interplay. Secondly, the algorithm's improved computational efficiency addresses the practical constraints of time and resources, a vital consideration in real-world applications.

In light of the evolving requirements in robotic design, where optimization tasks are increasingly complex and multidimensional, the advanced NSGA framework offers a more apt solution than traditional methods. Its ability to navigate through a vast solution space and identify a spectrum of optimal solutions caters to the dynamic and multifarious demands of modern robotic systems. Thus, our selection of this approach is not only justified but essential for achieving the nuanced and high-quality outcomes desired in this field of research.

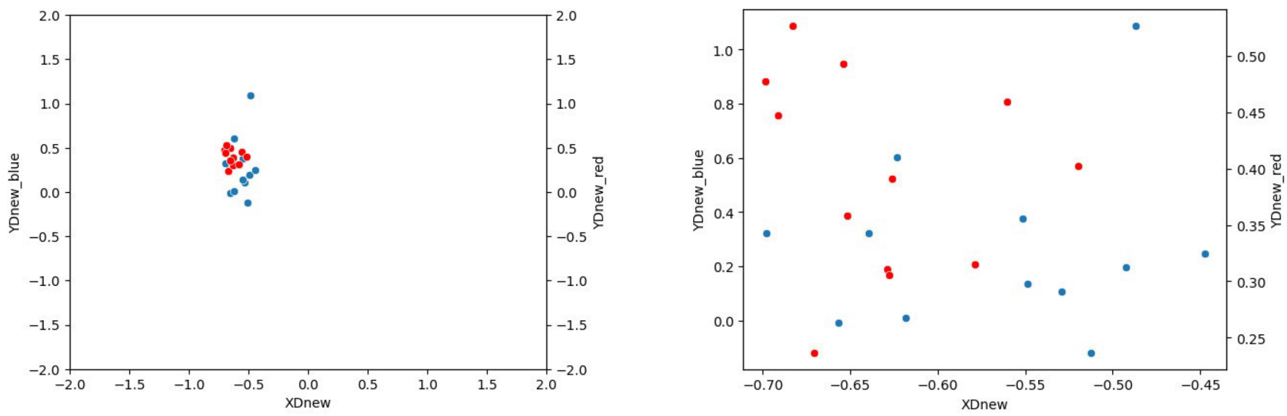
B. ADVANTAGES

Comprehensive Design Exploration: By employing the NSGA, our study ventured beyond the traditional singular optimal solution. Instead, it revealed a spectrum of Pareto-optimal solutions, each tailored to different design and performance criteria. This multi-solution landscape is particularly invaluable in real-world applications where design requirements may vary based on specific contexts [66].

Efficiency and Precision: Historical approaches, grounded predominantly in trial and error or heuristic methods, were both time-consuming and lacked precision [67]. The NSGA-driven methodology showcased in our study significantly expedited the design process while ensuring meticulous attention to detail and precision in the derived solutions.

Flexibility in Addressing Trade-offs: Robotic leg linkage design, as acknowledged in prior literature, is replete with trade-offs [68]. The NSGA's ability to simultaneously optimize multiple objectives enabled our study to flexibly navigate these trade-offs, resulting in designs that balance competing objectives like speed, stability, and energy efficiency.

Replicability and Scalability: The framework provided by our study ensures that the research findings are not confined to isolated instances. The established methodology



a) Scatter plot in full space

b) Scatter plot in partially space

FIGURE 11. Comparison of empirical solutions and the solutions generated by NSGA-II.

can be replicated across different robotic models and scaled to accommodate more complex design challenges, ensuring broader applicability and relevance.

C. EXPLORING ADVANCED OPTIMIZATION ALGORITHMS

The utilization of the NSGA algorithm in this study, while effective, represents just a fraction of the vast landscape of advanced optimization algorithms available for complex decision problems. Future research should encompass a broader spectrum of these algorithms, including hybrid heuristics, metaheuristics, adaptive algorithms, self-adaptive algorithms, island algorithms, polyploid algorithms, and hyperheuristics. These advanced methodologies have demonstrated significant efficacy across various domains, presenting a promising avenue for enhancing the decision-making process in our study's context.

For instance, hybrid heuristics, which combine the strengths of different optimization strategies, have shown remarkable success in online learning environments, optimizing learning paths and content delivery [69]. Similarly, in the realm of scheduling and multi-objective optimization, metaheuristics have provided flexible and robust solutions, adeptly balancing conflicting objectives [70], [71]. The transportation sector has benefited from adaptive algorithms, with their ability to adjust to dynamic environments and optimize routes and logistics [72].

In medical applications, self-adaptive algorithms have been instrumental in patient diagnosis and treatment planning, demonstrating their utility in high-stakes decision-making scenarios [73]. Moreover, the use of island algorithms in data classification has led to more accurate and efficient processing of large datasets, a crucial factor in domains like finance and cybersecurity [74].

The exploration of advanced optimization algorithms in this research opens avenues for addressing complex, large-scale optimization problems. One notable example is the Self-Adaptive Fast Fireworks Algorithm (SF-FWA) developed by Chen and Tan [75]. SF-FWA demonstrates significant efficiency in large-scale optimization, suggesting its potential applicability in optimizing intricate systems like robotic design. Its self-adaptive nature, which allows for dynamic adjustment to varying optimization landscapes, aligns well with the multifaceted challenges encountered in robotic locomotion.

Furthermore, the Adaptive Polyploid Memetic Algorithm, as explored by Dulebenets [76], offers a promising approach for scheduling and resource allocation problems. This algorithm's flexibility and adaptability could be instrumental in optimizing the scheduling of computational tasks in robotic systems, particularly in environments with high variability and complexity.

Singh et al. [77] provide insights into the development of heuristic optimization methods for safety improvement projects, dealing with conflicting objectives. Their approach to balancing multiple objectives effectively could be adapted for robotic systems where safety, efficiency, and energy consumption need to be optimized simultaneously.

Additionally, the study by Singh and Pillay [78] on ant-based pheromone spaces for generating constructive hyper-heuristics presents a novel approach to problem-solving. This method's ability to evolve and adapt to changing environments could be particularly beneficial for robotic systems operating in dynamic, unpredictable settings.

The potential applications of these advanced algorithms in the decision problem addressed in our study are manifold. For example, hybrid heuristics could offer a more nuanced approach to leg linkage design, combining the strengths of various optimization methods. Island algorithms, with their distributed processing capabilities, could enhance computational efficiency in multi-objective optimization tasks.

In conclusion, the exploration of these advanced optimization algorithms holds the key to unlocking more sophisticated and effective solutions for challenging decision problems. Future research should not only compare these advanced methodologies against our proposed approach but also investigate their potential to revolutionize the field of robotic design and beyond. This exploration, supported by relevant references, will broaden the horizon of possibilities in optimization strategies, paving the way for more innovative and impactful applications.

D. FUTURE PERSPECTIVES

Integration with Neural Networks: Inspired by recent advances in hybrid methodologies [71], future research could explore the amalgamation of NSGA with neural networks. Such a convergence could facilitate more adaptive and self-learning robotic designs, enhancing performance outcomes.

Real-world Testing and Validation: While our study laid significant theoretical and simulation-based groundwork, subsequent endeavors should prioritize extensive real-world testing. These empirical validations will not only reinforce the established findings but also offer insights into unforeseen challenges and opportunities.

Application Beyond Walking Robots: The principles and methodologies elucidated in our research, while tailored for walking robots, hold potential for broader robotic applications. Future studies could adapt the NSGA-driven framework for flying drones, swimming robots, or even multi-modal robotic systems [79].

Evolving the Algorithm: As the field of genetic algorithms continues to evolve, future research could harness more sophisticated versions of NSGA or even entirely novel algorithms. Such advancements could further refine the design outcomes and cater to emerging challenges in the domain of robotics.

Addressing Environmental and Ethical Implications: As robotics increasingly intersects with real-world applications, future perspectives must also encompass the environmental footprint of these designs and the ethical considerations of their deployment. Subsequent research could explore sustainable materials for leg linkage or delve into the socio-ethical implications of widespread robotic integration into human ecosystems.

Further investigation and refinement are warranted in several key areas of limb linkage design to advance walking robot technology. Firstly, the dynamic adaptability of limb linkages in varying terrain conditions requires deeper exploration to enhance robots' effectiveness in environments ranging from urban landscapes to uneven natural terrains. Secondly, the integration of sensory feedback mechanisms into limb design can be further refined to improve balance and interaction with surroundings. Additionally, material innovation in limb construction, focusing on lightweight yet durable composites, needs ongoing research to optimize performance and energy efficiency. Validation of these advancements through real-world testing and simulation models is essential to ensure their efficacy and readiness for future applications, including assistive robotics in healthcare, search and rescue operations in disaster relief, and exploratory missions in extraterrestrial environments.

In conclusion, our research, while shedding light on the transformative potential of NSGA in leg linkage design, has also sown the seeds for future inquiries. As we stand at the threshold of what can be termed the 'Robotic Renaissance', it is imperative that the synergy of design, algorithms, and ethical considerations guide the trajectory of innovations in this realm.

VII. CONCLUSION

The journey to optimize the leg linkage design of walking robots, entwining mechanics and computation, resonates with broader aspirations of human ingenuity. The endeavor to replicate and refine the elegance of natural locomotion is not merely a testament to our technological ambitions but also an ode to the wonders of biological evolution. This study, titled "Optimal Leg Linkage Design for Horizontal Propel of a Walking Robot Using Non-dominated Sorting Genetic Algorithm for Multiobjective Optimization in Multiple Selection," embarked on this quest with a dual focus: the marriage of practical design challenges with the computational prowess of the NSGA.

Our findings underscore the transformative potential of this convergence. Through the lens of the NSGA, the design landscape was illuminated with a spectrum of Pareto-optimal solutions, each balancing a myriad of objectives, from propulsion efficiency to stability. The significance of this multi-dimensional exploration cannot be understated, especially as robotics moves from confined labs to the diverse terrains of our planet.

However, as with any research endeavor, this study is but a stepping stone. While it has unraveled a tapestry of design possibilities, it also beckons further inquiries, refinements, and validations. The world of walking robots is on the brink of expansive horizons, with myriad applications awaiting—from healthcare and disaster relief to exploration of alien terrains. Moreover, as this future unfolds, it is studies like ours that will chart the course, ensuring that the robots of tomorrow walk with the grace, efficiency, and adaptability befitting their roles.

In sum, as we conclude our exploration, we are reminded that the quest for optimal design is perpetual. And while the solutions of today bring pride, it is the questions of tomorrow that ignite our collective imagination, driving the relentless march of science, technology, and innovation.

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