Tradeoff Between Area Coverage and Energy Usage of a Self-Reconfigurable Floor Cleaning Robot Based on User Preference

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ABSTRACT Floor cleaning robots have been developed to cope with the issues arisen with conventional cleaning methods that involve extensive human labor. hTetro is a self-reconfigurable floor cleaning robot that has been introduced to improve area coverage. Polyomino tiling theory is utilized by hTetro to plan area coverage. Energy usage and area coverage are distinct for different tiling arrangements, and they are often conflicting entities. Therefore, hTetro needs to maintain the tradeoff between area coverage and energy usage to improve its performance. This paper proposes a novel method to determine the tradeoff between area coverage and energy usage of a tiling theory-based self-reconfigurable floor cleaning robot per user preference. A linguistic option such as ''High coverage'' that represents user preference has uncertainty since fuzzy linguistic terms do not possess definitive meaning. Moreover, the meaning of such user preference depends on the present status of the robot. Thereby, a novel fuzzy inference system is proposed to determine the tradeoff between area coverage and energy usage by interpreting the meaning of user preference while accounting for the present status of the robot. A Weighted Sum Model (WSM) based Multiple-criteria decision-making (MCDM) method is adapted per user preference interpreted by the fuzzy inference system. The behavior of the proposed system has been evaluated considering heterogeneous test cases. The behavior of the test cases confirms the applicability of the proposed concept for adapting the tradeoff between area coverage and energy usage of a self-reconfigurable floor cleaning robot based on user preference.

INDEX TERMS Self-reconfigurable robot, cleaning robot, energy usage, area coverage, fuzzy linguistic information, user preference, human-friendly robotics.

I. INTRODUCTION

Constructions are intensively carried out in every part of the world to cater to the demands of the growing population [1]. These buildings and structures are usually cleaned by human labor to maintain the aesthetic appearance and living conditions. Cleaning is a monotonous activity that involves intensive human labor where productivity, cost, and safety are foremost worries. In addition to that, human labor is scarce and expensive due to socio-economic complexities [2]. Therefore, the attention of the robotic researchers has drifted toward the development of robots that can autonomously

handle diverse cleaning activities, including floor cleaning [3], staircase cleaning [4], facade cleaning [5], and garden cleaning [6].

Floor cleaning is one of the critical areas that demand the deployments of autonomous robots to carry out cleaning. In this regard, diverse aspects of floor cleaning robots have been studied and developed to improve the abilities of floor cleaning robots. For example, advanced path planning and navigation algorithms have been developed to enrich the coverage and navigation efficiency [7], [8]. Environment perceiving and sensing abilities of floor cleaning robots have also been improved to enhance the navigation abilities [9], [10]. In addition to that, many debris detection algorithms have been proposed for floor cleaning robots to improve cleaning

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activities [11], [12]. Enhancing cleaning efficiency through multi-robot coordination has also been investigated [13]. Apart from these core developments, human-robot interaction of floor cleaning has also been studied to improve the long-term deployment of floor cleaning robots in human-populated environments [14].

Most of the floor cleaning robots mentioned above have a fixed morphology. However, cleaning robots with fixed morphology face major challenges from the perspective of covering the cleaning area due to inaccessibility in narrow spaces during navigation. Developing self-reconfigurable robots that can shift the morphology to access narrow spaces is a promising solution to overcome the problem of coverage [15]. In this regard, Prabakaran *et al.* [16] proposed a self-reconfigurable floor cleaning robot named hTetro. hTetro is a Tetris inspired modular robot that can shift its morphology to mimic one-sided tetrominoes. Polyomino tiling theory has been utilized in this robot to solve the coverage problem [17]. The ability of reconfiguration to different morphologies allows hTetro to outperform the floor cleaning robot with fixed morphologies in the aspect of coverage.

Diverse aspects of hTetro have been studied to improve the abilities of this self-reconfigurable floor cleaning robot. In this regard, an approach based on graph theory to realize complete coverage path planning has been studied [18]. The realization of energy-optimized path planing for complete coverage has been addressed in [19]. Energy usage of hTetro, when reconfiguring from a shape to shape and navigation, has also been assessed in [20], [21]. Most of the existing approaches for reconfigurable cleaning robot uses polyominoes tiling theory to address the coverage problem. Polyominoes tiling theory introduces different tiling theorems that satisfy the complete coverage of the area considered for the tiling. Nevertheless, the area considered for the tiling should satisfy several constraints to entirely covered it by using these tiling theorems [22]–[24].

Typical shapes of floor areas considered for the cleaning would not be ideally matched with the spatial constraints required for a perfect tiling. Thereby, an area could not be covered entirely, and different tiling theorems cover the area to a different extent. On the other hand, the energy usage of different tiling arrangements is different from each other. The best tiling criterion for an area should be selected by analyzing energy usage and coverage of each tiling criterion. In this regard, the work [25] proposed a Multi-criteria Decision Making (MCDM) to select the best tiling arrangement. In the cited work, it assumes that the tradeoff between energy usage and area coverage is defined as one to one. However, the tradeoff between the area coverage and energy usage should be decided based on user preferences instead of having a fixed tradeoff. Moreover, the robot should allow a user to select the required tradeoff to improve human-friendliness. For example, a user should be allowed to select "high coverage". Most of the users of these robots do not have technological competencies, and this selection is preferred to be made linguistically without knowing the exact underlying. However,

user preference selected linguistically possesses uncertainty (fuzzy linguistic terms such as "high" and "low" do not possess definite quantitative meaning) based on the present status of the robot [26], [27].

Much research work has been done in the niche of interpretation of fuzzy linguistic information contained in user instructions in the form of terms such as "high" and "little" since the ability of a robot to understand such information is crucial for enhancing human-robot interaction [27], [28]. The proposed methods have been developed by utilizing fuzzy logic [29] and fuzzy neural networks [30]. These methods are capable of interpreting the fuzzy linguistic information by adapting the perception of a robot based on environment [28] and prior experience [30]. Nevertheless, the scopes of most of the state of the art methods are limited to cope only of linguistic terms related to distances [30], direction [31], speed of movements [26], and force on a surface [32]. Methods for interpreting fuzzy linguistic information related to aspects such as area coverage and energy have not been examined.

Therefore, this paper proposes a novel method to infer the tradeoff between energy usage and area coverage of a self-reconfigurable robot based on user preference. The tradeoff between energy usage and area coverage is inferred by a fuzzy inference system based on user input and the present status of the robot. The weighting parameters of an MCDM process are adapted based on the inferred tradeoff. Section II gives a brief about hTetro. The method proposed to tradeoff between area coverage and energy usage based on user preference is presented in Section III. Particulars on validation and behavior analysis are discussed in Section IV. Section IV summarizes the outcomes of the work.

II. ROBOT PLATFORM

hTetro is a self-reconfigurable robot inspired by the tile-matching puzzle game called "Tetris". It has a modular structure with four blocks, which can mimic the one-sided tetrominoes, as shown in Fig. 1. The seven shapes are named as "I", "L", "J", "S", "Z", "O", and "T". The shapes that are mimicked by hTetro are distinct since the pieces cannot be flipped. Nevertheless, rotation and translation operations can be performed on these 7 shapes. The hardware arrangement of hTetro is depicted in Fig. 2. Each block is squared shape with equal width and length of 25 cm. The four blocks are interconnected with three hinges that allow each module to have relative motions. hTetro can mimic the one-sided tetrominoes by shifting its morphology through rotations around the hinges. For navigation, the robot is equipped with geared DC motors. Arduino Mega controller is used to handle the low-level controlling functionality of the robot. For high-level controlling and processing tasks such as mapping and localization, a compute stick is deployed to the robot. A Lidar is used for mapping and localization purposes. It is expected to have cleaning units in all the modules to carry out the cleaning. Previous work on hTetro proved that this self-reconfiguration ability of hTetro improves the area coverage compared to a floor cleaning robot with fixed morphology [16].
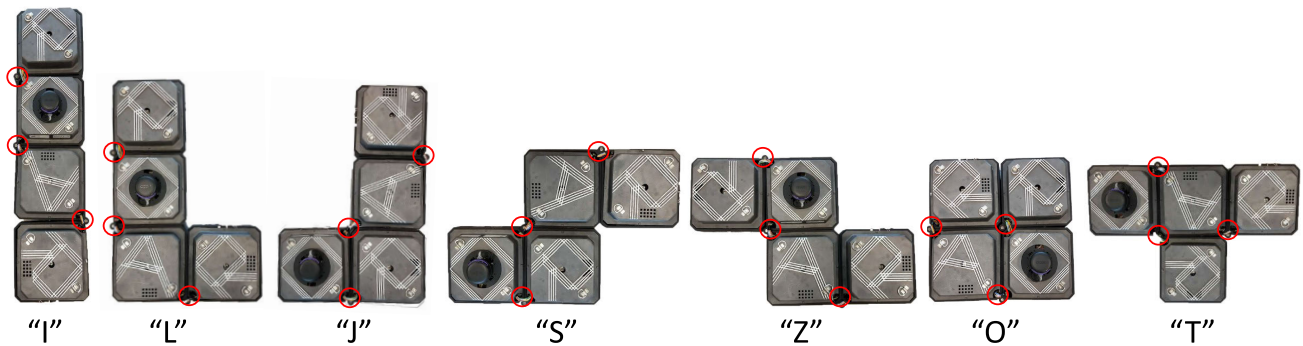
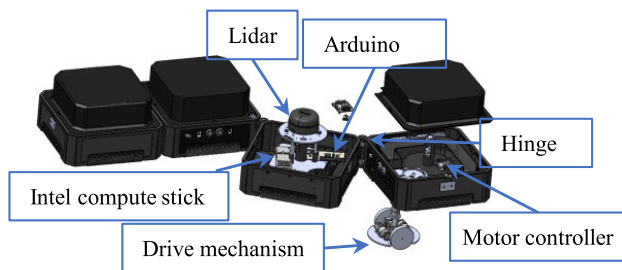**FIGURE 1.** hTetro in seven different one-sided tetrominoes. The location of hinges are annotated in circles.

FIGURE 2. Hardware arrangement of hTetro.

III. TRADEOFF BETWEEN ENERGY USAGE AND COVERAGE BASED ON USER PREFERENCE

A. TILING THEORY

The polyominoes tiling theory is a mathematical formulation that explains the constraints and potentials of completely tiling a space from a set of polyominoes. Since hTetro can mimic one-sided tetrominoes, tiling theories derived for tetrominoes can be used to design the coverage of a given floor environment for cleaning. Translation and rotation operation can be applied to the one-sided tetrominoes since hTetro can perform rotation and translation through the navigation system [16]. However, the flipping operation cannot be applied. Much mathematical work has been done in this specific niche to propose different tiling theorems [22]–[24]. Nevertheless, these tiling theorems impose hard constrains for realizing a perfect tiling arrangement for a given environment. For example, a theorem proposed in [22] indicates that a rectangular area $a \times b$ can be tilled from tetrominoes "T", "Z", and "S" if and only if either one side is divisible by 4 or $a, b = 2(mod\,4)$ and $a + b > 16$. Therefore, it would not be possible to perfectly tile a given area from the tetrominoes in all the situations. Regardless of this issue, previous work on hTetro proved that the area coverage of a self-reconfigurable floor cleaning robot could be improved through the tiling approach with respect to a robot with a fixed morphology [17].

B. MULTIPLE-CRITERIA DECISION-MAKING (MCDM)

Typical floor areas, which have to be cleaned by hTetro, are often occupied by objects. For example, various furniture and equipment could be placed in floor environments. In addition to that, floor areas have complex shapes. As a result of these matters, floor areas expected to be cleaned by the robot would not always be satisfied by the spatial constraint required for the tiling theorems mentioned in section III-A. Hence, a tiling arrangement generated for a particular floor would not entirely cover the floor area, and there would be uncovered spaces. A large number of different tiling arrangements for a particular environment can be generated by repeating the tiling pattern generation with the same set of tile pieces or by changing the set of tile pieces used for the tiling. Nevertheless, the coverage of tiling arrangements generated would be different, and none of the tiling arrangements would not be able to completely cover the area in some cases. On the other hand, the energy consumed by the robot when following different tiling arrangements would also be different. The energy usage of the robot depends on the tiling arrangement since the energy consumed by the robot during a shape-shifting varies in accordance with the present morphology and next morphology [20]. This situation is further explained from the following example situation, where two tiling arrangements are generated for a particular floor area. The first tiling arrangement has 89% area coverage with 58% energy usage while the second tiling arrangement has 91% coverage with 80% energy usage. If only the area coverage is considered, the second tiling arrangement is used by the robot despite the high energy usage, which is not desired. If only the energy usage was considered, it would also yield to undesired situations. For example, a situation where two tiling arrangements generated can be considered. The first tiling arrangement has an area coverage of 83% with an energy usage of 50%, while the second arrangement has an area coverage of 60% with an energy usage of 48%. If only the energy usage was considered, the robot would select the second arrangement. The energy usage and area coverage are conflicting criteria in selecting the most suitable tiling arrangement for a cleaning task.

Therefore, Multiple-criteria decision-making (MCDM) method [33] would be used to select the most suitable tiling arrangement that is used by the robot to clean a particular floor area. A Weighted Sum Model (WSM) [33] is used

in selecting the most suitable tiling arrangement among the possible alternatives. The goal of decision making should be maximizing the area coverage while minimizing energy usage. Therefore, WSM score of ith possible tiling arrangement for a particular case, A_i^{WSM} is defined as given in (1), where E_i and C_i are normalized energy usage and normalized area coverage of the ith tiling arrangement. $w_C \in [0, 1]$ and $w_E \in [0, 1]$ are scalar constants that decided the tradeoff between energy usage and area coverage. w_C and w_E are determined by a fuzzy inference system that interprets the user preference considering the present status of the robot (explained in III-C). The tiling arrangement, which has the maximum WSM score, is selected as the most suitable tiling arrangement in a particular case.

$$A_i^{WSM} = w_C C_i - w_E E_i \qquad (1)$$

C. INTERPRETATION OF USER PREFERENCE

The goal of the system is to decide the most suitable tiling arrangement based on two conflicting criteria, area coverage, and energy usage. The tradeoff between these two criteria is determined by adapting the weights, w_C, and w_E based on user preference. User preference is taken as an input through a user interface. Most of the users of hTetro are non-expert in technology. Non-expert users prefer to interact with robots through linguistically understandable inputs [27], [34]. Hence, user preference is taken as a selection from a set of linguistic terms. The three preferences, "High coverage", "Intermediate", and "Low energy" are given for a user to indicate his/her preference in a case. The fuzzy linguistic terms such as "high" and "low" do not have definitive quantitative meanings and the interpretation depends on the present status of the robot [27]. In this case, the meaning of these selection terms depends on the present battery level of the robot since the energy usage and coverage as a direct impact on it.

Fuzzy logic is a computational technique that can be used for transforming logical statements into a non-linear model [35], [36]. The powerful modeling ability of this technique allows it to cope with any complex behavior [35], [37], [38]. Fuzzy logic has a high power of cointensive precisiation, which is essential for the formalization of scientific concepts in human-centric fields [39]. In addition to that, fuzzy logic has proven to be effective in coping with dilemmas that consist of imprecise and incomplete process dynamics and data [40]–[42].

The meaning of fuzzy linguistic information contained in a user preference cannot be mathematically modeled due to the lack of underlying dynamics of a process. On the other hand, the necessary behavior in this scenario can be defined from a set of linguistic rules. Since fuzzy logic allows computation with linguistic rules, the meaning of user preference expressed from fuzzy linguistic information can be modeled using fuzzy logic. Furthermore, dilemmas that cannot be formulated mathematically such as to model human-like complex behavior, fuzzy logic can be applied
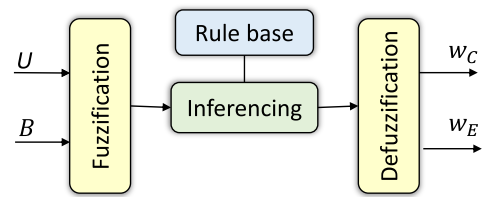

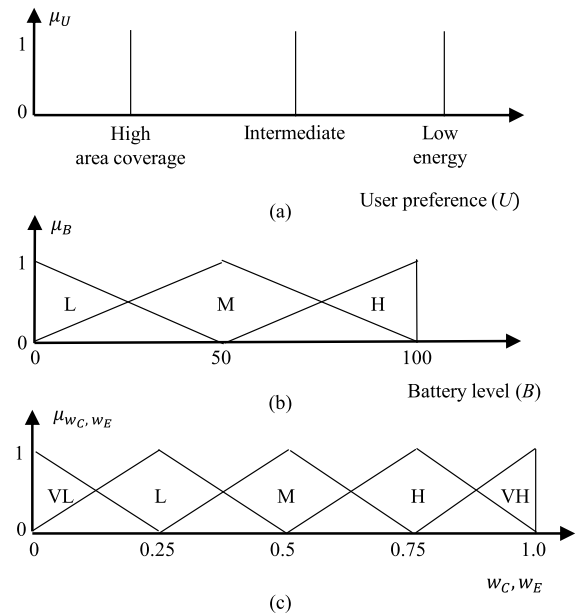**FIGURE 3.** Functional architecture of the fuzzy inference system.

FIGURE 4. Input and output membership functions of the fuzzy inference system for interpreting user preference. (a) Input membership function for user preference. (b) Input membership function for battery level. (C) Output membership function for w_C and w_E. It should be noted that the same sort of membership function is used for both output. Hence, only one is shown. The fuzzy labels are defined as VL: 'Very Low', L: 'Low', M: 'Medium', H: 'High', and VH: 'Very High'.

for better performance [34], [43]. Especially fuzzy logic is often used in the state of the art methods for interpreting fuzzy linguistic information contained in user preferences [27], [34]. Therefore, a fuzzy inference system is used to determine the tradeoff between energy usage and area coverage by interpreting user preference.

The functional architecture of the proposed fuzzy inference system is depicted in Fig. 3. The fuzzy inference system takes two inputs; user preference (U) and the battery level (B) of the robot to interpret user preference. These two inputs are fuzzified in the fuzzification layer by using the input membership functions. The input membership function for user preference is shown in Fig. 4(a). The input membership function for user preference has three singleton fuzzy sets to represents the three linguistic options available for a user to indicate user preference. The input membership function for the battery level has three triangular fuzzy sets, as shown in Fig. 4(b). The corresponding degrees of membership of the fuzzified inputs, U and B are defined as μ_U and μ_B, respectively. A set of if-then linguistic rules that defines the anticipated behavior of the fuzzy inference system is stored in the rule base.
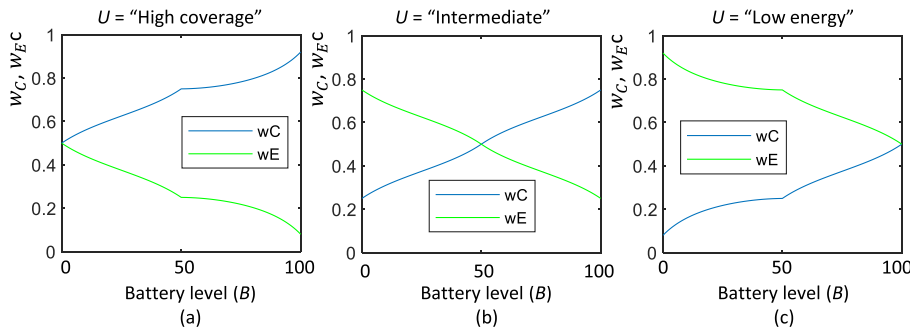
FIGURE 5. Expected variation of w_C and w_E with respective battery level (B) during different user preferences (U).

The rule base of the proposed fuzzy inference system is given in Table 1. The input space and output space are mapped by this rule base in the inferencing stage to synthesize the required behavior. The firing strength of ith rule, α_i can be obtained as in (2) considering minimum and maximum operators as the t-norm and t-conorm operators respectively [44].

$$\alpha_i = \min(\mu_{U_i}(U), \mu_{B_i}(B)) \qquad (2)$$

The fuzzy inference system has two outputs for w_C and w_E. The same sort of membership function is used for these two outputs. The corresponding output membership functions are shown in Fig. 4(c). The activation degree of ith output fuzzy set, $\mu_{w'_{X_i}}$ can be obtained as in (3) considering Mamdani implication [44]. Moreover, the corresponding fuzzy consequents are clipped by the respective firing strength of a rule. In here, it should be notated that w_X is either w_C or w_E. The fuzzy consequents of all the rules are accumulated to a single resultant fuzzy set, $\mu_{w'_X}(w_X)$ as given in (4) for each output, where n is the number of rules. The aggregated fuzzy consequents are defuzzified in the defuzzification layer to obtain the corresponding quantitative meanings. The center of the area method is used for the defuzzification of the two outputs. Thus, the defuzzified output could be obtained as in (5).

$$\mu_{w'_{X_i}}(w_X) = \min\{\alpha_i, \mu_{w_{X_i}}(w_X)\} \qquad (3)$$

$$\mu_{w'_X}(w_X) = \max\{\mu_{w'_{X_1}}(w_X), \mu_{w'_{X_2}}(w_X), \dots, \mu_{w'_{X_n}}(w_X)\}$$
$$\text{for } X = \{E, C\} \qquad (4)$$

$$w^*_X = \frac{\int w_X \mu_{w'_X}(w_X) dw_X}{\int \mu_{w'_X}(w_X) dw_X} \quad \text{for } X = \{E, C\} \qquad (5)$$

The weights of the WSM are adapted based on the defuzzified outputs. The expected variations of w_C and w_E (i.e., the weights of the WSM) in accordance with the battery level and user preferences are plotted in Fig. 5. The tradeoff between the area coverage and energy usage is dependent on these weights of the WSM.

D. OVERALL OPERATION
The overall operation of the robot is given in Algorithm 1. The robot should be initialized with a metric map of the

TABLE 1. Rule base of the fuzzy inference system.

User preference (U)	Battery level (B)		
	L	M	H
High coverage	$w\_C = M$ $w\_E = M$	$w\_C = H$ $w\_E = L$	$w\_C = VH$ $w\_E = VL$
Intermediate	$w\_C = L$ $w\_E = H$	$w\_C = M$ $w\_E = M$	$w\_C = H$ $w\_E = L$
Low energy	$w\_C = VL$ $w\_E = VH$	$w\_C = L$ $w\_E = H$	$w\_C = M$ $w\_E = M$

Algorithm 1 Operation Sequence

input : Metric Map, User Preference
output: Coverage Plan
Initialization;
Create occupancy grid map;
Generate N number of distinct tiling arrangement;
U = User Preference;
B = Check present battery level();
$[w_E, w_C]$ = Infer user preference(U, B);
while $i \leftarrow N$ **do**
    C_i = Area coverage(i^{th} tiling set);
    E_i = Energy usage(i^{th} tiling set);
    A_i^{WSM} = $w_C C_i - w_E E_i$;
end
Coverage Plan = argmax(A_i^{WSM})th tiling set;
Execute cleaning (Coverage Plan);

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environment that has been created from the lidar. The user preference that indicates the tradeoff between area coverage and energy usage is also taken as an input. After the initialization of the cleaning process, the robot generates the occupancy grid map of the environment, considering the size of one block as a grid cell. Then, N number of tiling arrangements for covering the generated occupancy grid map is generated based on tiling theory and backtracking algorithms by the robot considering 7 one-sided tetrominoes. The robot checks the present battery level of the robot before evaluating the meaning of the user preference. The constants, w_e and w_c, which decide the tradeoff between energy usage and area coverage, are retrieved by feeding the user preference and present battery level to the fuzzy inference system. The robot calculates the energy usage (E) and area coverage (C) of
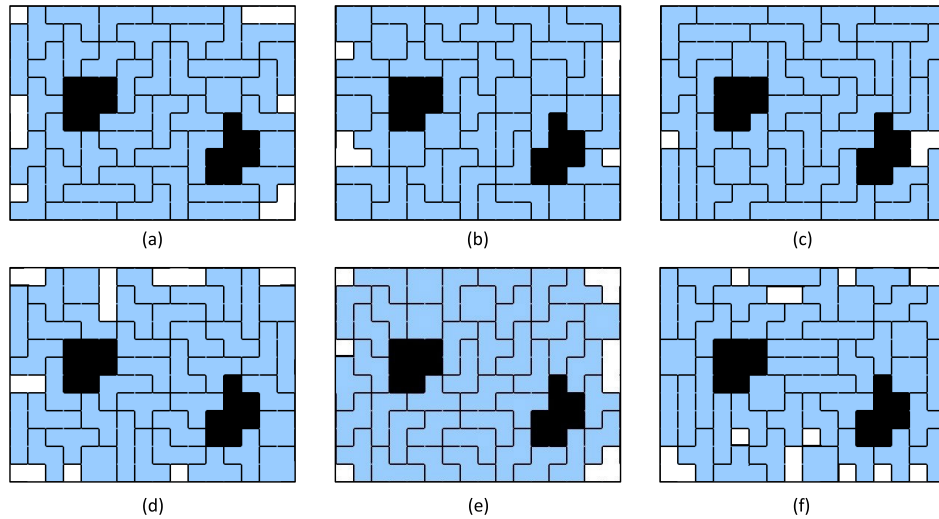
FIGURE 6. The tiling arrangements generated by the robot. The color code has following meaning; black: areas occupied by objects, blue: areas to be tilled by the robot, and white: uncovered areas.

the ith tiling arrangement. Energy usage of the robot for a tiling arrangement is calculated based on the energy model of hTetro given in [20]. The corresponding WSM score is then calculated. This calculation is repeated for $i = 1$ to $i = N$. The tiling set, which has the highest WSM score, is finally selected as the coverage plan for the particular scenario. Then, the robot starts the execution of the cleaning based on the selected coverage plan. It should be noted that all the steps from the initialization to the execution of the cleaning are internal processes of the robot.

IV. RESULTS AND DISCUSSION
A. VALIDATION PROCEDURE
A 4 m X 3 m floor area with randomly placed objects has been considered to validate the behavior of the proposed concept. A pre-created map of the environment was fed to the robot. The floor area is yielding to a grid of 16×12. The total floor area was 12 m^2, and 1 m^2 out of this area was occupied with objects. Many tiling arrangements to cover the floor area can be generated for a given floor. For the sake of simplicity of explanation and analysis, the number of tiling arrangements internally generated by the robot was kept to six ($N = 6$). The generated six tiling arrangements are shown in Fig. 6. Five heterogeneous cases with different user preferences and statuses of the robot were considered for the analysis of determining the tradeoff between area coverage and energy usage by the proposed method. These cases were created by intentionally configuring the battery level of the robot and user preferences.

B. RESULTS AND ANALYSIS
The normalized area coverage and energy usage calculated for the generated six tiling arrangements are given in Table 2. The values for the area coverage (C_i) was normalized by considering the maximum area coverage obtained from the

TABLE 2. Area coverage and energy usage of the generated tiling arrangements.

i	Figure	C_i (%)	E_i (%)	Utilized shapes
1	Fig.(a)	95	92	{I, O, L, J, T, Z, S}
2	Fig.(b)	97	81	{O,J, T}
3	Fig.(c)	100	85	{I, O, L, J, T, Z, S}
4	Fig.(d)	93	84	{I, O, L, J, T, Z, S}
5	Fig.(e)	95	100	{O, J, T, Z, S}
6	Fig.(f)	93	67	{I, O, J, Z, S}

arrangement 3 (actual area coverage of the tiling arrangement 3 was 98%). Similarly, energy usage (E_i) was normalized by considering tiling arrangement 5, which had the highest energy usage.

Two user preferences during different battery status of the robot have been considered to evaluate the effects on the tradeoff between area coverage and energy usage in accordance with user preferences. Altogether 5 heterogeneous cases were gathered for the analysis. The user preference (U) and the battery level (B) for the considered 5 cases are given in Table 3. The weights of the WSM (i.e., w_C and w_E) determined by the fuzzy inference systems for the corresponding cases are also given in Table 3. The WSM scores (A_i^{WSM}) obtained for the six different tiling arrangements for the five test cases are given in Table 4. The tiling arrangement, which has the maximum WSM score, is selected as the most suitable tiling arrangement for a particular case. The WSM score of the tiling arrangement selected for each case is annotated by a bounding box.

In case 1, the user preference was "High coverage". The battery level of the robot was 90%. The fuzzy inference system interpreted the meaning of "High coverage" as a 0.839 to 0.161 tradeoff between area coverage and energy usage (i.e., $w_C = 0.839$ and $w_E = 0.161$) by accounting the present battery level of the robot. Moreover, it prioritized the area coverage as preferred by the user. Therefore, the

TABLE 3. Variation of w_C and w_E in the considered cases.

case	U	B	w_C	w_E
1	"High coverage"	90%	0.839	0.161
2	"High coverage"	55%	0.752	0.248
3	"High coverage"	20%	0.604	0.396
4	"Low energy"	90%	0.438	0.562
5	"Low energy"	55%	0.282	0.718

TABLE 4. Variation of A_i^{WSM} in generated tiling arrangements for the considered cases.

tiling arrangement (i)	A_i^{WSM}				
	case 1	case 2	case 3	case 4	case 5
1	64.893	48.624	20.948	-10.094	-39.266
2	68.342	52.856	26.512	-3.036	-30.804
3	70.215	54.12	26.74	-3.97	-32.83
4	64.503	49.104	22.908	-6.474	-34.086
5	63.605	46.64	17.78	-14.59	-45.01
6	67.24	53.32	29.64	3.08	-21.88

The most suitable arrangement that is selected by the robot in each case is bounded by a box.

tiling arrangement 3 (i.e., $i = 3$) got the highest WSM score ($A_3^{WSM} = 70.215$) and hence, the tiling arrangement 3, which has a normalized area coverage of 100% and a normalized energy usage of 85%, was selected as the most suitable tiling arrangement in this case. In case 2, the battery level of the robot and the user preference were considered as 55% and 'High coverage', respectively. As a result of this lower battery level, the WSM had a lower ratio between the area coverage and the energy usage than case 1 (w_C and w_E were 0.752 and 0.248 respectively). Moreover, biased toward the area coverage was lowered compared to case 1 due to the reduced battery level. Nevertheless, the tiling arrangement 3 was selected as the most suitable arrangement in this case since the MCDM method still has a biased toward the coverage. Therefore, the behavior of cases 1 and 2 validates the robot's ability to comply with user preference in cases where there are no concerns over the present battery level of the robot.

In case 3, the user preference was kept the same as case 1 and 2. However, the battery level was considered as 20%. The bias toward the coverage was reduced by the fuzzy inference system by accounting for the low battery level of the robot. Hence, the tiling arrangement 6, which had a low energy usage with adequate area coverage, got the highest WSM score yielding to got it to be selected as the most suitable tiling arrangement in case 3. This case validates that the robot is capable of interpreting the user preference by accounting the present status of the robot to adapt its interpretation of user preferences.

In cases 4 and 5, the user preference was 'Low energy'. Therefore, the WSM was biased toward the energy usage by the fuzzy inference system in case 4 (w_C and w_E were 0.438 and 0.562 respectively). In case 5, the bias toward energy usage was boosted as a result of lower battery level (w_C and w_E were 0.282 and 0.718 respectively). Therefore, the tiling arrangement 6 was selected as the most suitable tiling arrangement in case 4 and 5 since it has a very low energy usage compared to others while having an acceptable area coverage. This behavior confirms the ability of the robot to

adapt the tradeoff between area coverage and energy usage in accordance with user preference while accounting for the present battery status of the robot.

Overall, the proposed method is capable of determining the tradeoff between area coverage of a reconfigurable floor cleaning robot based on user preference. Most of the state of the art methods of reconfigurable robot considers the energy usage and area coverage as two distinct problems, and those methods attempted to optimize only one criterion either energy usage [20], [21] or area coverage [18], [19]. The work [25] proposed a method to optimize both energy usage and area coverage using a Multi-Criteria Decision Making (MCDM) method. However, the cited work assumes that the tradeoff between the area coverage and energy usage is one to one. In contrast, the method proposed in this paper allows a user to indicate his/her preference in deterring the tradeoff. Thereby, the proposed method makes a novel contribution to state of the art by proposing a method to determine the tradeoff between energy usage and area coverage based on user preference.

According to [45], most of the users of floor cleaning robots do not have many technical competencies. Therefore, human-friendly features are expected from the floor cleaning robot for acceptance for long-term usage [14], [46]. The ability of the robot to consider user preference for determining the tradeoff between energy usage and area coverage would improve the human-friendliness of a floor cleaning robot. Therefore, the work proposed in this paper improves the human-friendliness of the existing reconfigurable floor cleaning robot since the existing floor cleaning robot does not possess this sort of ability.

Mainly, allowing to indicate user preference as a linguistical selection instead of a numerical indicator is vastly contributed to improving the human-friendliness of a floor cleaning robot [27]. However, user preference indicated from a linguistic term is uncertain since fuzzy linguistic terms such as 'high' do not have a definite meaning. State of the art approaches for interpreting fuzzy linguistic information have been developed to interpret fuzzy linguistic information related to energy usage or area coverage [27]. Therefore, the work proposed in this paper is also contributed to improving state of the art in coping with fuzzy linguistic information contained in user instructions by robots.

The concept proposed in this paper has been developed and validated using hTetro. hTetro is one of the versatile robots in a class of reconfigurable tiling robots that have been developed to improve the area coverage. The versatility of hTetro is the main reason for considering hTetro for the work presented in this paper. Nevertheless, the application of the proposed method to other tiling robots is straightforward since the operation of the robot. Further investigations in this direction are proposed for future work.

V. CONCLUSIONS

Area coverage and energy usage of a reconfigurable floor cleaning robot are often conflicting entities. A cleaning robot

needs to maintain a proper tradeoff between area coverage and energy usage to ascertain a superior operation. Therefore, this paper proposes a method to determine the tradeoff between area coverage and the energy usage of a reconfigurable floor cleaning robot based on user preference.

User preference expressed through linguistical options possesses uncertainty since fuzzy linguistic terms such as 'high' and 'low' do not have a definitive meaning. The exact meaning of fuzzy linguistic terms related to the operations of a robot depends on the present status of the robot. Thereby, a novel fuzzy inference system is proposed to interpret user preference by accounting the status of the robot for determining the tradeoff between area coverage and energy usage. A Multiple-criteria decision-making (MCDM) algorithm built on a Weighted Sum Model (WSM) is adapted in accordance with the tradeoff determined by the fuzzy inference system to select the most suitable tiling arrangement for a particular scenario. MCDM algorithm determines the most suitable tiling arrangement for a particular scenario by evaluating different tiling arrangements for area coverage and energy usage.

The behavior and the performance of the proposed concept in determining the tradeoff between area coverage and energy usage of a self-reconfigurable floor cleaning robot have been accessed considering intentionally created test cases. According to the results, the proposed concept is capable of adapting the tradeoff between area coverage and energy usage based on user preference while accounting for the present status of the robot. Moreover, the behavior of the test cases validates the real-world applicability of the proposed concept.

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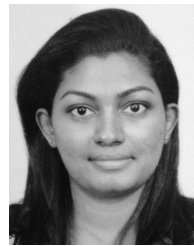
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