Perspective

Toward Sustainable Mars Exploration: A Perspective on Collaborative Intelligent Systems

Thomas Janssen [1,*], Ritesh Kumar Singh [1], Phil Reiter [2], Anuj Justus Rajappa [1], Priyesh Pappinisseri Puluckul [1], Mohmmadsadegh Mokhtari [2], Mohammad Hasan Rahmani [1], Erik Mannens [2], Jeroen Famaey [2] and Maarten Weyn [1]

[1] IDLab-Faculty of Applied Engineering, University of Antwerp-imec, Sint-Pietersvliet 7, 2000 Antwerp, Belgium; riteshkumar.singh@uantwerpen.be (R.K.S.); anuj.justusrajappa@uantwerpen.be (A.J.R.); priyesh.pappinisseripuluckul@uantwerpen.be (P.P.P.); mohammad.rahmani@uantwerpen.be (M.H.R.); maarten.weyn@uantwerpen.be (M.W.)

[2] IDLab-Department of Computer Science, University of Antwerp-imec, Sint-Pietersvliet 7, 2000 Antwerp, Belgium; phil.reiter@uantwerpen.be (P.R.); mohmmadsadegh.mokhtari@uantwerpen.be (M.M.); erik.mannens@uantwerpen.be (E.M.); jeroen.famaey@uantwerpen.be (J.F.)

[*] Correspondence: thomas.janssen@uantwerpen.be

Abstract: Mars has long captivated the human imagination as a potential destination for settlement and scientific exploration. After deploying individual rovers, the next step in our journey to Mars is the autonomous exploration of the Red Planet using a collaborative swarm of rovers, drones, and satellites. This concept paper envisions a sustainable Mars exploration scenario featuring energy-aware, collaborative, and autonomous vehicles, including rovers, drones, and satellites, operating around Mars. The proposed framework is designed to address key challenges in energy management, edge intelligence, communication, sensing, resource-aware task scheduling, and radiation hardening. This work not only identifies these critical areas of research but also proposes novel technological solutions drawn from terrestrial advancements to extend their application to extraterrestrial exploration.

Keywords: batteryless sensing; collaborative vehicles; robot swarms; edge AI; energy-awareness; energy harvesting; Mars exploration

1. Introduction

Mars, alongside the Moon, represents one of the most compelling frontiers in space exploration. The quest to explore Mars is driven by our innate curiosity to uncover the mysteries of the cosmos, seek signs of ancient life, and investigate the possibility of human habitability.

Currently, there are two autonomous vehicles from the National Aeronautics and Space Administration (NASA) actively exploring Mars: *Curiosity* and *Perseverance*. *Curiosity* investigates the Martian climate and geology, searching for signs of planetary habitability [1]. The more recently launched *Perseverance* rover carries several scientific instruments, cameras, sensors, and the first Mars helicopter *Ingenuity* [2]. *Perseverance* collects rock and soil samples with the goal of seeking evidence of former microbial life and preparing for human exploration missions [3].

As listed in Table 1, many other Mars exploration missions are planned worldwide. For example, within the *ExoMars* program of the European Space Agency (ESA), the *Rosalind Franklin* rover will search for the existence of past life on Mars by analyzing underground

samples [4]. The mission was scheduled to launch in 2022 but due to geopolitical tensions, it will not start before 2028. Another noteworthy mission is the *Mars Sample Return* mission, in which *Perseverance* will collect samples using a robotic arm developed by ESA. The mission aims to collect the samples and return them to Martian orbit through the first rocket (*Mars Ascent Vehicle*) launched from Mars. This will in turn be captured by the *Earth Return Orbiter*, which finally returns to Earth [5].

Table 1. Overview of active, inactive, and planned Mars rover missions.

| Rover	Country (Agency)	Status	Year	Notes
Sojourner	USA (NASA)	Inactive	1997	Part of Mars Pathfinder mission; operated for 85 days.
Spirit	USA (NASA)	Inactive	2004	Last contact in 2010; explored Gusev Crater.
Opportunity	USA (NASA)	Inactive	2004	Lost in a 2018 dust storm after nearly 15 years.
Curiosity	USA (NASA)	Active	2012	Nuclear-powered; ongoing science in Gale Crater.
Perseverance	USA (NASA)	Active	2021	Operating in Jezero Crater; collecting rock samples.
Zhurong	China (CNSA)	Inactive	2021	Entered hibernation in 2022; presumed inactive.
Rosalind Franklin	Europe (ESA)	Planned	2030	Delayed ExoMars rover; will search for signs of past life.
Tianwen-3	China (CNSA)	Planned	2030	Mars sample return mission.
Sample Recovery Helicopters	USA (NASA)	Planned	2030	Autonomous vehicles to assist in sample return.
IDEX (IDEFIX)	France/Germany (CNES/DLR)	Planned	2027	Will study Mars' moon Phobos; part of MMX mission.
Mangalyaan-2	India (ISRO)	Planned	2026	Orbiter, lander, rover, and helicopter; direct Mars entry with sky crane landing.

Robustness, flexibility, and scalability represent the key bio-inspired attributes that are desirable in swarm robotic systems [6]. Robustness shows the capacity of the system to withstand variations in different environmental conditions despite failures in the individuals. Flexibility ensures the system's capacity to provide solutions for diverse tasks through various coordination strategies. Finally, scalability implies the practicality of adjusting the size of a swarm system.

Applying swarm systems on Mars is even more challenging. For swarms to operate on Mars, the system must be highly autonomous, as Mars-to-Earth communications may take as long as 22 min. As a result, for a swarm mission on Mars, not only must robustness, flexibility, and scalability be optimized, but fault detection and diagnosis (FDD) need to be managed by the system itself. Limitations in such a setup imply that the FDD must take place locally, be computationally lightweight, and remain quick and accurate [7].

The goal of this paper is neither to provide a comprehensive literature review on Mars exploration missions like [8,9] nor to present experimental results. Instead, our goal for this concept paper is to provide a futuristic vision of how to explore Mars in a sustainable manner. In the future, we envision that multiple rovers, drones, and satellites will be exploring Mars collaboratively. This raises the idea of collaborative vehicles, with the aim

to complete their tasks as effectively and efficiently as possible. As a key contribution to the state of the art, we provide an overview of the research challenges involved with deploying such vehicle swarms on Mars. Inspired by terrestrial-based advancements, we suggest technological solutions for sustainable and efficient robotic exploration of the Red Planet.

The remainder of this paper is visually outlined in Figure 1 and structured as follows. Section 2 describes the expected application scenario in which rovers, drones, and satellites all work together for effective and efficient Mars exploration. Following the key components of NASA's Mars infrastructure [10], Sections 3–5 discuss novel technologies and paradigms for energy management, communication, and collaborative task scheduling, respectively. The way forward is discussed in Sections 6 and 7 concludes the paper.
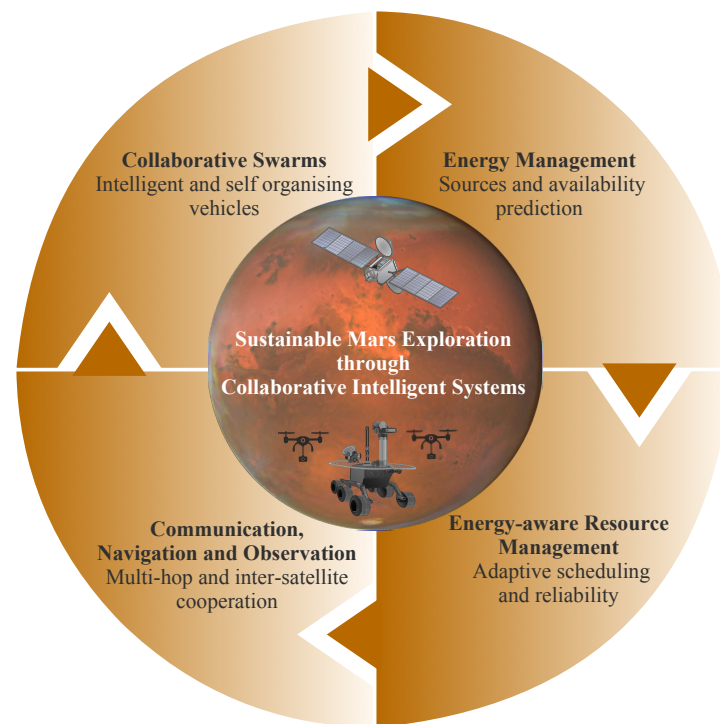

Figure 1. Overview of key concepts required for collaborative intelligent systems for sustainable Mars exploration in this work.

2. Application Scenario

Imagine a futuristic scenario in which tens or even hundreds of autonomous vehicles are working together on Mars. In this work, the terms *autonomous vehicles* and *swarm* encompass the various types of robotic and remote sensing devices used for exploration and research purposes, including rovers on the surface, aerial drones, and satellites orbiting Mars. As we illustrated in Figure 2, this swarm of vehicles facilitates the collection of in situ resources for geological surveys and/or building infrastructure [11]. High-level tasks could include the following:

- Explore, monitor, and map remote Martian areas to find useful geological resources.
- Retrieve useful resources and samples, e.g., by drilling holes in the Martian surface.
- Transport resources from measurement locations to a central collection point.
- Construct and maintain habitats, e.g., by 3D printing using collected resources.
- Repair and maintain other vehicles in an autonomous fashion, i.e., search and rescue of a rover.
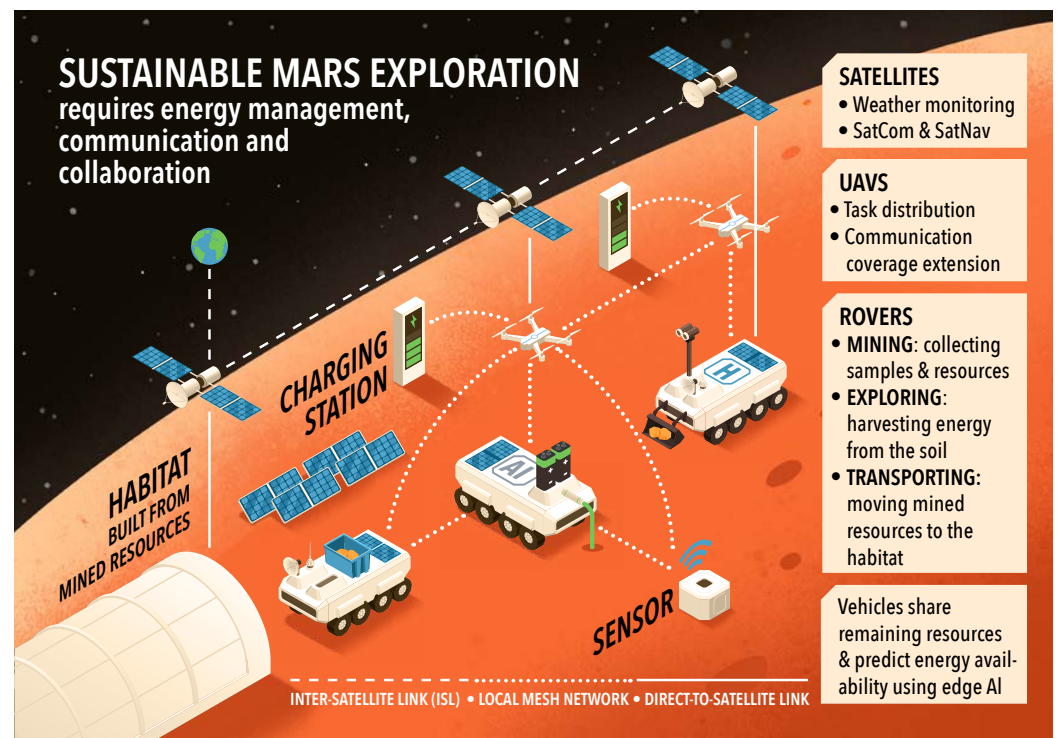
Figure 2. Visualization of the envisioned scenario with architecture and functional description of the collaborative energy-aware sensors, rovers, drones, and satellites on Mars in this work.

Cooperation between the robotic explorers currently on Mars is limited. However, as the number of autonomous vehicles increases, there will be a need for more cooperation. As the vehicles are assigned different tasks requiring varying amounts of resources, they will benefit from communication and resource sharing. More specifically, a swarm of vehicles will be able to better deal with resource constraints and energy limitations compared to a scenario in which vehicles need to perform all tasks individually. To illustrate the benefits of vehicle cooperation in the use case of geological surveys (i.e., collecting resources and analyzing samples), the remainder of this section provides some concrete examples.

2.1. Sampling and Mining Rovers

Based on energy availability, distance and Estimated Time of Arrival (ETA) to a location of interest, the swarm of rovers negotiates which rover(s) will collect samples or mine resources. In addition, the rovers communicate their availability to the swarm of autonomous vehicles. Upon task completion, a transporting rover will be selected similarly, which then collects the samples or mined resources and moves them to the Martian base, where other rovers can use them to analyze samples or to build infrastructure. When there is insufficient energy available, rovers will negotiate new task allocations, requesting others to take over. When the 'next shift' arrives, the rover stops its task and proceeds to recharge itself.

2.2. Drone Exploration

Another example is the collaboration between rovers and drones. Due to the rough Martian surface, rovers travel extremely slowly. Perseverance holds the current record for the longest single-day drive: 319 m in one sol (i.e., Martian day). Drones can fly much faster. The Ingenuity mission demonstrated that a drone could travel a horizontal distance of 625 m in a single flight of 166 s at a maximum speed of 5 m/s on Mars [2]. Hence, drones can construct a detailed map of the area and quickly identify the most optimal route to usable resources, using onboard intelligence. Resource locations are transmitted to the

nearest rover(s) and spread over the swarm of autonomous vehicles through wireless mesh communication. In addition, the drones may also have the capability to fly to hard-to-reach areas and collect soil samples, in case no rovers are available or when they simply cannot reach the area of interest.

2.3. Satellite Relay

A final case where inter-vehicle cooperation helps is when the distance between robotic explorers prevents direct or mesh communication. In this case, a network of satellites can facilitate communication between distant rovers. In addition, the satellites also serve as relays for communication back to Earth.

Thus, in the envisioned scenario, the key aspect for efficient and effective Mars exploration is the collaboration between the rovers, drones, and satellites. The next sections dive deeper into how this can be facilitated.

3. Energy Management

Space exploration systems deployed millions of kilometers away from Earth need a reliable source of energy to sustain their operation. While electrochemical cells might suffice for powering short-term deployments, long-term missions demand alternative sources of energy to provide periodic energy top-ups to the system. Often, long-term space missions rely on energy generated from sources such as solar or nuclear, in combination with rechargeable electrochemical cells [12,13]. These sources are not always readily available; they are rather limited and unpredictable in many scenarios. Consequently, there is an increasing demand for reliable sources of energy and advanced energy management systems in space missions.

3.1. Conventional Energy Sources

Solar radiation and heat energy generated from the natural decay of radioactive materials have been the predominant energy sources for the majority of Mars rover missions. During the early days of Mars explorations, solar energy was the standard choice due to its well-established technology and ease of implementation. Converting solar energy to electrical energy can be easily accomplished with the help of solar cells. Typically, a combination of solar cells with rechargeable batteries is used. The rechargeable batteries act as a backup source and supply energy to the system when the Sun stops illuminating the panel. For instance, NASA's *Mars Pathfinder* used gallium–arsenide solar cells with a maximum production of 180 W in combination with 27 V, 40 A h silver–zinc batteries [14]. Similarly, many other solar energy-powered rovers were deployed.

The selection of **solar energy** for powering Mars rovers was primarily motivated by their widespread use in many space applications and satellites, as well as the technological maturity it has gained over time. However, the Martian environment presented several challenges that restricted the performance of solar panels:

1. The intensity of solar radiation decreases with the distance from the Sun to a planet. Consequently, Mars receives weaker illumination from the Sun due to its relatively distant placement in the solar system.
2. Relying on solar energy limits choices for the landing location of the rover to those close to the equator, where the radiation is abundantly available [15].
3. A major factor that negatively impacts the performance of solar cells is the occurrence of frequent dust storms and dust devils on Mars. These dust storms lead to the accumulation of dust particles over the cells, resulting in the degradation of their performance. The fact that dust particles in the Martian atmosphere are electrostatic further elevates the concern [16]. Over time, the accumulation of dust particles on

solar cells has led to the temporary or permanent failure of several missions. Cleaning of dust particles caused by local turbulence has been highly beneficial in mitigating the impact of gradually accumulating dust during certain surface missions reliant on solar power. However, predicting these events has proven to be challenging. In April 2022, NASA's Ingenuity Helicopter became inactive for around 6 days as the solar arrays stopped functioning due to dust cover [2]. In another instance, China's first Mars rover *Zhurong*, surrendered to dust storms [17]. The rover was commanded down to sleep mode in response to an expected dust storm, but it never woke up from its sleep.

In an attempt to overcome the limitations of solar energy sources, **Radioisotope Thermal Generators (RTG)** were introduced [18]. RTGs are nuclear generators that rely on heat energy released during the radioactive decay of materials to generate electricity. Though RTGs are nuclear power generators, they are direct converters and do not rely on moving or mechanical converters to generate electricity. Specifically, an RTG uses solid-state heat engines, called thermoelectric generators (TEG), to convert heat produced from the natural decay of radioactive materials into electricity. When heat passes through two dissimilar metals that are joined together, a voltage is generated at the junction of these two materials. This phenomenon is known as the Seebeck effect and lays the foundation for TEGs [19].

The use of RTGs has significant benefits. The lack of moving parts to convert heat energy into electrical energy enables a compact, maintenance-free, and noiseless design for RTGs. Moreover, unlike solar cells, they are not impacted by the atmospheric conditions of Mars, such as dust storms. Considering these advantages, many missions to Mars have started using RTGs as energy generators. For example, the Curiosity rover, which has been operational on Mars since August 2012, is sustained by an RTG that guarantees a lifetime of a Martian year (i.e., 687 Earth days) or more [20].

While RTGs address many drawbacks associated with solar power generators, they also have limitations of their own. A significant drawback of the RTG is its low efficiency, cost, and scarcity of radioactive materials. A reduced efficiency exaggerates the amount of heat input and hence the quantity of radioactive material required to produce sufficient electrical energy. Most of the designs so far achieved a beginning-of-life (BOL) efficiency of only 6% [21]. In addition, as the efficiency of a TEG decreases with temperature differences, the RTG will see a decline in its efficiency and power output with time. Although there were proposals for advanced stirling radioisotope generators (ASRG) that claimed to increase efficiency, these proposals were not realized [22].

Finally, there are serious concerns over the influence of RTGs on the local atmospheric environment and consequently, over the meteorological data gathered by the measurement system [23]. Therefore, RTGs must adhere to several regulatory frameworks to ensure system safety, both during the launch and while on Mars [24]. For example, the Moon Treaty does not explicitly prohibit the use of nuclear power sources such as RTGs but emphasizes the need for environmental protection and notification of activities that might harm others or the space environment [25].

3.2. Alternative Energy Sources

At present, Mars exploration missions are relatively limited in terms of the number of rovers deployed and the extent of collaborative swarming activities. Nevertheless, as we progress toward a scenario illustrated in Figure 2, the energy demand is bound to increase. Although solar and RTG power generators are capable of powering autonomous vehicles, their applications are limited due to the drawbacks discussed before. Consequently, a dense and deeply collaborative ecosystem of autonomous vehicles would need to include

alternative sources of energy to ensure a long-term operation. To accomplish this, it is necessary to build a multi-source energy harvesting system and employ an efficient power management scheme capable of handling solar, RTG, and other durable energy sources resilient to the challenging conditions on Mars.

Thermal energy generators possess the unique capability of generating energy from temperature differences, making them reliable for energy generation in applications where such differences are available. There are many thermal energy reservoirs identified on Earth that can be potential sources for thermal energy harvesting. Among these, the temperature difference between Earth's soil and air is considered a viable source of energy that can power many applications [26,27]. Earth's soil has a high thermal inertia, causing its temperature to lag behind air temperature. This leads to a consistent temperature difference, which can be converted into electrical energy.

When exploring the ground and atmosphere temperature from Mars, a similar phenomenon can be observed [28]. For instance, the data collected by the Curiosity rover show the atmosphere temperature changing from −2 °C to −75 °C, while the surface temperature can go as high as −3 °C and as low as −91 °C [29]. Moreover, soil temperature on Mars lags behind the atmospheric temperature, creating a noticeable temperature difference that can be converted into electrical energy with the help of a TEG. While the energy produced from the soil–atmosphere temperature difference may not be sufficient to perform energy-demanding tasks, many real-time monitoring and surveillance applications may benefit from it.

Although TEGs can convert temperature gradients into energy, they can only work with spatial gradients. Thus, extracting a temperature gradient between the atmosphere and the ground surface requires installing a heat engine with one of its heat reservoirs connected to the atmosphere and the other connected to the soil. This limits the mobility of the energy generators. If this temporal difference could be converted into energy, it could serve as an energy source for autonomous vehicles. A conversion of temporal temperature difference into electrical energy can be accomplished with thermal resonators [30]. Thermal resonators typically employ two thermal masses, for instance, phase change materials (PCMs), to create a thermal circuit tuned to a particular temperature fluctuation frequency, converting temporal gradients into spatial gradients [30]. This spatial gradient can be then converted into energy with the help of any heat engine, or it could even be transformed into mechanical energy to actuate autonomous vehicles [31].

Converting thermal energy to electric energy using TEG is a relatively inefficient process [19]. Consequently, the power generated by thermal generators from ambient heat sources on Mars may not be sufficient to compensate for the solar energy blackout during dust storms. While dust storms reduce the efficiency of solar generators, they themselves can be a potential source of energy. Mars's environment is abundant in mechanical vibrations produced by frequent winds and dust storms, making this **vibrational energy** a valuable resource.

However, traditional electromagnetic generators may not be the right choice for Mars due to their heavy weight and large form factor, which results in an increased cost of transportation. Instead, lightweight **Triboelectric Nanogenerators (TENG)** could be an alternative for converting these mechanical vibrations into electrical energy [32,33]. Unlike mechanical converters, TENGs do not rely on electromagnetic conversion but use electrical charge transfer due to the triboelectric effect. Therefore, TENGs do not require permanent magnets and coils, which contribute significantly to the weight of traditional wind energy generators.

A comparison of energy generators and sources discussed so far is presented in Table 2. It is worth noting that this represents only a subset of energy sources. There are several

sources yet to be exploited or discovered. For instance, there have been discussions on the feasibility of **geothermal energy** [34] as well as **sublimation heat engines** based on the Leidenfrost effect for generating energy [35]. Sublimation heat engines propose the use of locally available dry ice on Mars's surface to convert temperature differences into rotational motion. Additionally, systems like **thermal wadis**, which have already been proposed for Moon missions may also find use in the Martian atmosphere [36].

Although there are many potential sources of energy native to the Martian environment, tapping energy from these sources for powering Mars missions and autonomous vehicles presents numerous challenges. In addition to the inherent inefficiencies associated with the energy converters, the harsh and not yet completely understood Martian environment imposes many restrictions.

Thermoelectric generators (TEGs) are known to be highly inefficient energy converters, particularly at low temperature differences, where their efficiency can even drop below 1%. Furthermore, most of the materials used for building TEGs are not suited for subzero temperatures [37,38], whereas the temperature on Mars can be as low as −91 °C at night. Hence, the choice of material for TEG and its effectiveness becomes a critical question.

Similarly, the thin atmosphere and reduced atmospheric pressure raise questions about the possibilities of **wind energy generators**. Because of this concern, the possibility of wind energy generation has often been overlooked for Mars applications.

Thus, more research and investigation need to be directed toward sustainable and efficient energy sources and generators for Mars. Nevertheless, it is improbable that a single energy source suffices all the energy demands on Mars. Instead, a combination of multiple energy sources complementing each other will provide a consistent and reliable energy system.

Table 2. Comparison of conventional and alternative energy sources and generators for Mars exploration.

| Generator	Benefits	Limitations	SoTA for Mars
Solar Panel	• Inexpensive • Portable •High power conversion efficiency (up to 28%) [12] • Mature technology	• Accumulations of dust cover impacts efficiency • Frequent maintenance required • Decreased radiation intensity—36 to 52% compared to Earth [39]	Used for Mars rovers
RTG	• All-weather operation • Minimum or no maintenance required • 6–7% of efficiency [21]	• Uses radioactive materials • Influence on local environment and acquired data • Not suitable for lightweight rovers	Used for Mars rovers
Ambient Heat-TEG	• No environmental impact • Least impacted by dust-storms • Least maintenance required	• Low efficiency • Low power density • Portability depends on the choice of heat source	Still in research phase
TENG	• No environmental impact • Dust storms are advantageous • Lightweight	• Low efficiency • Impacted by weather conditions • Not a well-established technology	Still in research phase

3.3. Energy Prediction

Selecting an appropriate source of energy is crucial in extraterrestrial missions. Yet another useful strategy in energy management is adjusting energy expenditure in accordance with energy availability. For instance, in systems powered only by electrochemical batteries, measuring energy availability can be as simple as measuring the battery's open circuit voltage. This measurement, combined with the certainty that energy does not inherently increase in a battery over time (unless recharged), provides us with the maximum energy available in a system for its future operations. Combining this knowledge with the energy consumed by various tasks of the system can help in formulating an apt strategy for task execution, thus achieving considerate management of the available energy.

However, the complexity in measuring the maximum amount of available energy for future operations of the system increases when the energy in the batteries can be replenished from ambient sources such as solar, thermal, or wind power, due to the uncertainty in the ambient source's availability. For instance, the uncertainty in solar, thermal, and wind power is introduced by factors such as the relative position and orientation of the system with respect to the energy source, solar activity, seasonal effects, and the weather conditions of the atmosphere containing the system. This uncertainty means that the maximum amount of available energy can change in the future from its present value in a non-linear fashion. Energy harvesting systems draw the required energy from ambient sources. As energy harvesting systems depend on these sources, the success of a task in terms of executing before the deadline with sufficient energy can depend on the accuracy of the estimations of available future energy [40]. Energy harvesting allows systems to be designed with reduced battery sizes or even replace batteries with enduring capacitors (i.e., battery-less systems) for improved sustainability.

Multiple works have been conducted to predict the energy available for energy harvesting systems on Earth [41,42]. These works include statistical models, such as auto-regressive integrated moving average (ARIMA), exponentially weighted moving average (EWMA), weather conditioned moving average (WCMA), profile energy prediction (Pro-Energy), and machine learning (ML) algorithms such as neural networks, Q-learning, and random forests. Depending on when in the future the accumulated energy value needs to be predicted, the prediction horizon can range from seconds to days [42]. A more sophisticated forecasting algorithm is required for accurate prediction when the prediction horizon is distant, as simple models such as ARIMA tend to have prediction errors that are approximately proportional to the prediction horizon.

While the above techniques have been applied in terrestrial environments, similar prediction models can also be applied on Mars, as illustrated in Figure 3. Martian environments have two significant conditions, namely, clear sky and dust stormy sky. However, the limited availability of Martian meteorological data and the extreme weather conditions on the planet make designing such time series forecasting models challenging. Synthetic data generation and online learning forecasting models can be used to alleviate this problem [43]. Nagle-McNaughton et al. describe how such generated data can both enrich existing Martian datasets with additional synthetic samples based on actual observations, as well as augment datasets for which samples are scarce with generated examples that approximate those on Mars [44]. These models can help Martian vehicles anticipate the quantity of available energy and accordingly adjust the current energy expense to maintain the reserve energy. The synthetic dataset can build upon the years of Martian meteorological results collected by the Mars Climate Database [45]. Section 5.2 describes next-generation, low-power AI methods that are suited to the requirements of adapting to the radically changing conditions in extreme environments.
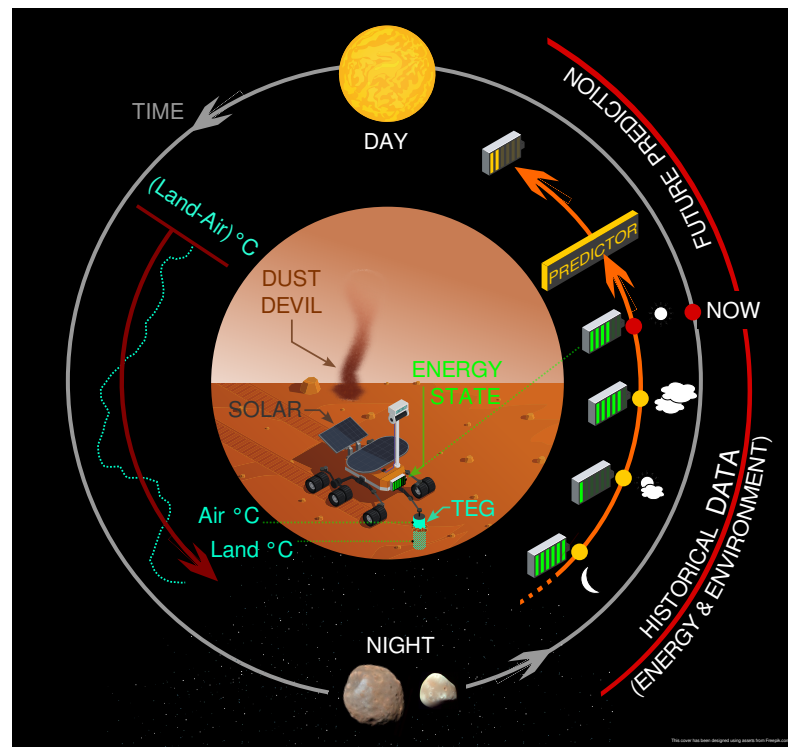
Figure 3. Based on our study, machine learning algorithms combine historical data of energy harvesting techniques and atmospheric conditions to predict available energy levels from different sources of energy on Mars.

4. Communication, Navigation, and Observation

Sustainable Mars exploration demands energy-aware and efficient communication, navigation, and observation. On one hand, local wireless technologies and protocols are required to facilitate the communication between rovers, drones, and in situ sensors deployed on Mars. On the other hand, a satellite constellation around Mars offers communication on a larger scale. In addition, such a constellation can also offer navigational guidance and remote sensing capabilities. These paradigms are discussed in the following subsections.

4.1. Multi-Hop Communication

The lack of a wired backbone communication infrastructure on Mars presents communication challenges related to long-range communication, necessitating multi-hop data relays through intermediary nodes. Tailored communication protocols strategically address these factors to optimize data transmission and seamless swarm connectivity. Simultaneously, the implementation of efficient routing algorithms plays a crucial role in enabling intelligent path selection. These algorithms consider dynamic elements, such as energy consumption and resource availability, ultimately leading to optimal data dissemination routes. An ad hoc network approach for Mars sensor networks utilizes a multi-path routing scheme with energy-aware and load-balanced node selection [46]. The base station, operated by a Mars lander or rover, polls sensor nodes periodically, establishing multiple paths with equal minimal hop distance. Path selection, based on random or neighbor energy usage, enhances data delivery reliability and reduces congestion. Simulation results showcase energy conservation and a more equitable distribution of energy consumption, significantly extending the network's lifetime, particularly with the superior performance of the energy-aware multi-path scheme.

Furthermore, the significance of fault tolerance and network resilience takes center stage, with a focus on integrating error correction mechanisms and self-healing strategies

to uphold communication integrity amid potential system disruptions. Another challenge is that these swarms of vehicles will be fully decentralized and will require very scalable and dynamic mesh or multi-hop communications as the swarm can be large, dense, and full of mobile nodes. To augment capacity utilization and network performance, strategies encompassing traffic management, network planning, and resource allocation tailored to the Martian environment come to the forefront. As mobility gains prominence, seamless hand-offs to facilitate adaptive and dynamic network topologies become indispensable. Cumulatively, these aspects spanning protocol design, routing algorithms, fault tolerance, mobility support, and network optimization underscore the pivotal role of multi-hop communication in empowering collaborative swarms to adeptly traverse and explore the dynamic landscape of Mars, enhancing the potential for successful exploration and efficient resource utilization.

4.2. Satellite Communication

While multi-hop mesh networks can dynamically extend network coverage through the movement of nodes, there is a limit to their communication range. Currently, the *Mars Express* orbiter of ESA and the *Mars Reconnaissance* orbiter of NASA, among others, provide connectivity to the Mars rovers on a larger scale [8]. Moreover, the orbiters help explore future landing sites. However, a full constellation of Mars orbiters is required to provide full coverage to all future ground- and air-based vehicles across the surface of Mars [47]. In this regard, SpaceX has recently pitched 'Marslink', a version of Starlink for the Red Planet [48]. For example, when a rover is exploring a new area and loses the local mesh communication signal, it can automatically fall back to a direct-to-satellite link to keep communicating observations. The latter can subsequently be forwarded through inter-satellite links (ISL).

In addition to the need for a larger antenna, the drawback associated with a direct-to-satellite communication link lies in its elevated energy consumption. A similar energy-intensive characteristic is observed with respect to the costly satellite link established for communication back to Earth. In order to counter this, low-power edge artificial intelligence (AI) algorithms can reduce the need for bandwidth-intensive and expensive downlinks through automated decision-making onboard satellites.

4.3. Satellite Navigation

Apart from telecommunication purposes, Mars orbiters can also feature navigation capabilities, creating a global navigation satellite system (GNSS) such as GPS or Galileo on Mars. Similar to the developments of Low Earth Orbit Positioning, Navigation and Timing (LEO-PNT) services on Earth [49–51], either a pseudoranging or Doppler positioning algorithm can be adopted to deploy PNT services on Mars. However, challenges exist in precise orbit determination, hardware radiation hardening, and dealing with different environmental conditions.

As part of the Artemis program, NASA presented the Cislunar Autonomous Positioning System Technology Operations and Navigation Experiment (CAPSTONE) mission, in which a peer-to-peer navigation technology incorporates relative tracking between two or more vehicles on the Moon, i.e., orbiters, landers, and rovers. This reduces the need for ground-based tracking stations, which is of particular interest for deep space exploration. Moreover, the navigation performance increases with the number of participating vehicles, which motivates the use of a CAPS-like system for a vehicle swarm on Mars.

Finally, when visual references are unavailable and cameras fail due to a lack of light, dust, or other obscurities, a Light detection, altimetry and velocimetry (LiDAV) sensor can

serve as a primary navigation input [52]. All these technologies will contribute to guiding rovers, drones, and satellites via the most optimal route, avoiding collisions and obstacles.

4.4. Mars Observation

Further Martian explorations and ventures towards human habitation will require increasingly autonomous systems that can operate independently without the need for interventions from Earth-based operators. The current generation of Mars rovers landed in easily accessible areas on Mars. However, large areas of Mars, such as the poles, remain unexplored due to difficult terrain and harsh weather conditions. This further motivates the need for a constellation of satellites observing Mars, predicting extreme weather events such as dust storms, identifying water and fuel sources, and facilitating surface operations.

Global space agencies are positioning to include AI technologies within future missions, ranging from collaborative satellite networks to autonomous extraterrestrial landscape exploration. ESA Discovery's OPS-SAT program is focused on integrating AI advancements to improve spacecraft onboard operations, enhance remote-sensing quality, and augment inter-satellite and satellite-to-Earth communications [53]. NASA's Artificial Intelligence Group is also developing autonomous spacecraft capabilities, including through their "Continuous Activity Scheduling Planning Execution and Replanning", or CASPER, initiative [54]. A recurring hurdle encountered by these international space research teams in deploying AI in orbit, on the Moon, or other planets is this technology's reliance on high-performance compute infrastructures.

Ensuring that the autonomous intelligence systems on Mars vehicles are optimized for inherent compute, memory, and power constraints is paramount to performing complex AI. Neural network (NN) compression, specifically context-aware NN pruning, reduces the size of NNs to the bare skeleton of what is required to correctly perform predictions of interest [55]. Neural architecture search (NAS) can also identify the most suitable NN for a specific task [56]. NAS coupled with advanced compression creates NNs that can perform under severely resource-limited conditions. Such research is being applied to onboard, near-sensor processing for future intelligent Earth observation satellite platforms, with obvious extensions to observations and spectral analyses of the Martian landscape [57].

For satellites, intelligent sensor fusion can permit both active and passive imaging instrumentation to enrich observations through the sharing of a single algorithmic stack, thus minimizing hardware costs and power requirements. For ground agents that can be impacted by Martian dust storms, for example, automated switching between sensors can be performed when required, such as focusing on radar measurements when atmospheric obstructions prevent the use of visual cameras and LiDAR [58]. A machine learning model is trained to operate on a single, common sensing representation, thereby saving resources while analyzing streams from different sensors in parallel.

5. Collaborative Energy-Aware Computing

5.1. Energy-Aware Task Scheduling and Distributed Computing

In a scenario where a swarm of autonomous vehicles is deployed on Mars for exploration and colonization, a major challenge arises: Unlike on Earth, there is no readily available power supply distribution network on Mars. In this novel and challenging environment, the robotic workforce must swiftly establish both mobile and fixed charging stations to ensure their *survivability* [59]. To tackle this challenge, a swarm of intelligent autonomous vehicles can employ cutting-edge AI-based scheduling algorithms to assign tasks while ensuring secure energy availability across the fleet of highly mobile and precisely sensing rovers. For instance, drones equipped with AI capabilities can manage the

optimal recharging of other vehicles' batteries through methods like wireless charging or battery replacement while partaking in the soil sampling tasks.

As described in Section 2, each vehicle possesses a diverse set of capabilities, ranging from resource extraction to scientific exploration. Given the energy-intensive and unpredictable nature of tasks on Mars, along with the limited available resources, an autonomous, energy-aware dynamic task allocation system [60] can be deployed to efficiently manage task scheduling. This system autonomously allocates tasks based on real-time assessments of each vehicle's capabilities and available energy, ensuring efficient task execution while maintaining a secure energy flow among the ambiently powered vehicles.

The autonomous nature of the task allocation system ensures that once task information is provided, it can perfectly handle the task execution without requiring continuous input from Earth. However, it is important to note that the Earth control system should monitor task accomplishments on a periodic basis, ensuring that the task's progress is aligned with mission objectives and verifying the successful completion of tasks and update the tasks list. This combination of autonomy and Earth-based monitoring ensures continuous, adaptive operations while accounting for the communication latency and disruptions inherent to Mars missions [61]. This approach involves the real-time assignment of tasks based on available resources, while being demonstrably resilient to robot failures and changes in environmental conditions [59].

The complex task allocation problem falls within the realm of online scheduling—a dynamic process requiring real-time adaptation of tasks to maximize efficiency. In the context of Martian exploration, efficiency refers to the ability to accomplish tasks and missions with minimal resource consumption, particularly in terms of time. The primary efficiency parameters revolve around minimizing the total time required to complete missions and tasks on Mars while adhering to constraints related to the availability of energy resources.

To mitigate the risk of robotic failures, such as those experienced in NASA's earlier missions, one potential solution is to implement a redundant, low-power energy management module [62] among the collaborative robotic systems. This module would monitor efficient energy harvesting mechanisms, facilitate dead-battery robot recovery, and provide a hard reset capability for the robots. Additionally, incorporating low-power communication protocols, such as Zigbee or Bluetooth Mesh, could enhance coordination and data sharing among robots while minimizing energy consumption.

Mathematically, metaheuristic algorithms are a feasible solution for addressing scheduling problems due to their ability to tackle NP-hard (non-deterministic polynomial-time hard) computational complexities. Despite the absence of a guarantee for globally optimized solutions, metaheuristic models have gained considerable attention in optimization domains [63]. This adoption can be attributed to their adeptness in an equilibrium between temporal efficiency and solution efficacy. This feature makes these methods appealing because they can identify effective solutions, even when the search for the absolute best solution would require an impractical amount of time or computational resources [64]. These advanced algorithms, inspired by natural processes like genetic evolution and particle swarm behavior, optimize the sequence of tasks in time and the distribution of tasks among robots, while considering energy constraints. Furthermore, adaptive AI models, like reinforcement learning (RL), embedded within the swarm's architecture would allow vehicles to learn and adapt to Mars' unpredictable energy patterns, making the allocation process more efficient over time by incorporating accurate energy prediction.

When considering the architecture for managing the complex interplay of tasks and energy allocation in UAV swarms, the choice between centralized and decentralized approaches becomes pivotal. In a centralized architecture, a central control unit makes

decisions for the entire swarm, whereas in a decentralized system, individual UAVs are empowered with decision-making capabilities, creating a more distributed and adaptive structure. On Mars, the advantages of a decentralized architecture are particularly pronounced due to the lack of immediate communication infrastructure and the vast, unpredictable environment, which make centralized control difficult to implement. This decentralized approach enables UAVs to operate autonomously, adapt to changing conditions, and recover from failures, ensuring continued functionality despite the challenges posed by the Martian environment [65]. A decentralized approach allows each vehicle to autonomously assess its energy levels, prioritize tasks, and collaborate with others when necessary—ensuring adaptability to the unique energy dynamics of Mars. Decentralization also reduces the risk of single points of failure, enhancing the system's overall robustness and scalability [66]. Furthermore, these intelligent robots, guided by algorithms that continuously learn and evolve, can be deployed in a collaborative human–robot environment, which is known as one of the industry 5.0 principles [67].

5.2. Next-Generation Low-Power AI

The AI paradigm prevalent at the time of this writing is centered on obtaining dramatically impressive results at the expense of grand computational costs and power consumption. Migrating the large-scale computing and power infrastructures required to maintain these data center facilities off-planet would require the establishment of power generation plants or the discovery of sources of high energy on or around Mars. Moreover, frequent communication to terrestrial data centers would be infeasible for real-time missions due to the high data transmission latencies and bandwidth requirements between Mars and Earth. As such, remote, resource-efficient AI algorithms are the only tenable solution for extraterrestrial applications of AI [68]. Applications of such AI algorithms for Mars operations include atmospheric and soil composition analyses, automated detection and decision-making from sensory inputs, pathfinding and exploration, as well as situation- and energy-aware management of resources.

Research on methods for reducing the compute and power requirements of ML algorithms is being spearheaded by numerous organizations, including the prominent TinyML community. Advancements have been made in algorithmic quantization, compression, and automated optimization techniques to reduce the processing, memory, and energy footprints of common ML models to operate on a variety of low-power devices, ranging from embedded processors to microcontrollers.

Quantization decreases model size through a reduction in the precision of values being stored and computed, while compression prunes away unnecessary model elements or determines an alternative, more compact representation. Automated generation and optimization of ML models aims to use ML to create, configure, and tune models to specific application, device, and resource requirements. Each of these methods aims to squeeze ML algorithms into ever-smaller size and energy form factors with minimal loss in model accuracy and precision; however, they are still bound by the restricted performance capabilities of conventional low-power computing elements, and the inefficiencies of traditional computing and programming paradigms applied to on-device ML. A next generation of brain-inspired computing is required.

In modeling the mammalian brain's signaling through event-based, electrical impulses, spiking neural networks operate under a resource footprint that is a marginal fraction of their artificial NN counterparts. Implemented as recurrently connected liquid state machines (LSMs), such networks can perform very low-power learning while attaining state-of-the-art levels of performance and accuracy without biologically implausible backpropagation [69].

As an alternative method of condensing observations into highly compact representations for AI processing, hyperdimensional computing (HDC) makes use of very long vectors–often ten thousand values or more–as concept embeddings. Such dense, information-rich representations can be transmitted, manipulated, and computed extremely efficiently, resulting in far less processing, memory, and storage requirements to achieve results on par with traditional compute paradigms [70].

These next-generation AI algorithms all still require thousands to millions of observational data examples from Mars to be trained properly. Neuromorphic algorithms, such as SNNs and HDCs, are suitable for rapid, low-power, on-device adaptation to previously unseen circumstances; however, they must still have a baseline training from Martian data. This need for more data was introduced earlier in Section 3.3. Since ground observations from Mars are, at the time of this writing, sparse and very costly to obtain from the few rovers currently making their way across the Red Planet, we propose synthetic data generation techniques, including generative AI, to supplement our present Martian datasets with generated, virtual samples that are based on known examples. The adaptability and generalizability of AI models are only as good as their foundational training data, so it is imperative that we gather and generate more Martian observations. As we facilitate a growing number of future Mars missions, we will hopefully also collect more data for AI training, and a positive feedback loop will be established for the field of autonomous Mars exploration.

5.3. Radiation Hardening

When designing systems for extraterrestrial missions, important considerations include adequate device shielding, radiation effects (cosmic rays and secondary particles), and material impurities, such as radioisotopes in chip packaging [71]. These can cause malfunctions in electronic devices that can be classified into three categories: total ionization dosage, displacement damage dosage, and single-event effects [72]. While hardware optimizations, such as using bipolar integrated circuits and wide band-gap substrates [73], can contribute towards radiation hardening, software optimizations can also be used in cases of single event effects. These can lead to transient faults that can cause soft errors, where a bit in the memory can be flipped from zero to one or vice versa.

While industry-standard methods, such as triple module redundancy (TMR) [74], can be applied to improve the tolerance against soft errors in low-resource overhead tasks, resource consumption becomes enormous when a similar technique is applied for heavy computing tasks, particularly executing AI algorithms. Hence, multiple optimization techniques have been proposed both at the hardware and software levels to improve the fault tolerance of AI algorithms [75]. One such technique for neural networks is called selective multiply-accumulate zero optimization (SMART), where the multiply-accumulate operation associated with a neuron is skipped if the input value is zero [76]. Other techniques such as fault-masking and activation clipping have also been proposed to improve the fault tolerance of AI [75]. These techniques can be used to improve the radiation hardening of various AI tasks executed by the robotic swarms on Mars while remaining energy efficient.

6. The Way Forward

This work describes a futuristic scenario in which a collaborative swarm of autonomous and intelligent vehicles enables sustainable Mars exploration. While it is crucial to identify key challenges, risks, and opportunities at an early stage, the authors are aware that such a scenario on Mars is only feasible after the following steps have been taken.

The first step towards this scenario is to create similar applications for collaborative swarms closer to home, i.e., on Earth or the Moon. This strategy is in line with ESA's *Terra Novae* roadmap and NASA's *Moon to Mars* strategy. One of the key objectives of the former is the human exploration of the Moon's surface on long-duration missions by 2030 [77]. This involves building habitation modules of the so-called lunar gateway, which will enable refueling and critical communication functions. Furthermore, ESA will start the design and development of Argonaut, a large lunar lander for the delivery of scientific payloads, rovers, and infrastructure.

As a perspective paper, this work does not propose an immediate implementation plan but instead outlines a structured research roadmap that identifies the key advancements required for sustainable Mars exploration. A phased approach is essential, progressing from theoretical studies and terrestrial technology development to lunar demonstrations and eventual Martian deployment.

The initial phase of research should focus on leveraging advancements in energy-aware autonomous systems, multi-agent coordination, energy-harvesting, and communication protocols, refining these technologies through **terrestrial simulations and analog environments** that replicate Mars-like conditions. This includes evaluating edge intelligence frameworks, energy-efficient networking, and autonomous navigation algorithms in controlled terrestrial settings before extending them to extraterrestrial applications.

Following terrestrial research, the next stage involves investigating the feasibility of integrating these systems into upcoming **lunar exploration** missions. The Lunar Gateway, along with ESA's Argonaut lander and planned surface habitats, presents an opportunity to test communication architectures and resource-aware task scheduling in a relevant space environment. Insights from lunar operations will provide a critical bridge toward adapting these technologies for the Martian context.

Finally, the transition to **Mars-focused research** will involve theoretical modeling, system-level simulations, and concept validation through precursor missions, enabling incremental adaptation to the unique environmental constraints of the Red Planet. This phase will explore strategies for radiation-hardened autonomy, energy-adaptive decision-making, cooperative robotic exploration, (self-)recovery of vehicles, and recycling of debris, ensuring that the proposed framework aligns with future Mars mission architectures and space sustainability goals. In line, the next step in ESA's roadmap is the sustainable exploration of the Moon in the subsequent decade, ultimately leading to the first human mission to Mars [78].

Designing Martian applications will involve (1) building a digital twin to simulate Martian conditions for prototyping and verification purposes, and (2) designing testbeds to develop and evaluate the proposed technologies. For example, radiation hardening experiments conducted on Earth can be designed to mimic the radiation on Mars to understand and quantify the impact on the device under test.

Energy management is one of the most crucial aspects to ensure sustainable Mars exploration. The next steps in this field involve selecting more sustainable energy sources and predicting the amount of available energy. The latter can be further improved by collecting data from various locations on the Red Planet to correlate parameters such as temperature difference between soil and atmosphere, solar irradiation at surface level at different angles, wind velocity with seasons, weather, day of the year, etc.

The rapid acceleration of near-Earth satellite and terrestrial autonomous vehicle deployments sets the stage for these technologies to be leveraged for the Moon and Mars. Increasing the onboard ML and sensing capabilities of both satellites and vehicles for terrestrial use directly translates to more effective, efficient, and intelligent systems for Mars exploration, observation, and habitation.

While this concept paper primarily focuses on the technical and engineering aspects of sustainable Mars exploration, it is essential to situate these developments within the broader context of cosmic and Earth-space sustainability. Recent initiatives by organizations such as NASA and the Secure World Foundation have highlighted the importance of ethical, legal, and environmental considerations in space activities. For instance, NASA's Space Sustainability Strategy outlines a framework for responsible space operations [79], and the Secure World Foundation has published resources addressing challenges in ensuring the security, safety, and sustainability of outer space activities [80]. These discussions encompass topics like planetary protection, space debris mitigation, and the long-term stewardship of extraterrestrial environments. Although a comprehensive analysis of these ethical dimensions is beyond the scope of this paper, we acknowledge their significance and emphasize that future work should integrate these considerations into international regulatory frameworks to ensure responsible and sustainable exploration of Mars.

7. Conclusions

In the quest to extend human presence beyond Earth, Mars has emerged as an appealing destination for exploration and potential colonization. However, the challenges of surviving and thriving on the Red Planet are immense, from its harsh environment to the vast distances that separate it from our home planet.

In contrast to the few standalone explorers on Mars today, we envision a swarm of drones, rovers, and satellites collaborating closely to achieve efficient and effective Mars exploration. Energy management, communication, navigation, observation, and collaborative energy-aware computing were identified as the key ingredients to reach this goal.

The goal of this work is neither to provide a comprehensive literature review on Mars exploration nor to present experimental results. Instead, we aim to provide a forward-thinking and comprehensive vision of sustainable Mars exploration through collaborative intelligent systems that set the foundations for and assist eventual human habitation of the Red Planet.

This work is written from a technological applications engineering perspective. Achieving sustainable Mars exploration requires knowledge and ideas from many other research domains, including material sciences (e.g., sustainability of materials) and robotics (e.g., how to control a swarm of drones on Mars). Hence, further interdisciplinary research is needed, fostering cutting-edge technologies that propel the boundaries of human exploration further into the cosmos.

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