Bu-Ali Sina University

Biosystems Engineering & Sustainable Technologies (BEST)

Journal Homepage: www.best.basu.ac.ir/
BEST J., 2(1) (2025) 11-19
DOI: https://doi.org/10.22084/best.2025.30904.1008

Simulation and Optimization of Wheeled Electric Robots and its Effects to Achieve Sustainable Development

Gader Balkipor *, Yusof Abbaspour Gilandeh

Department of Biosystem Engineering, University of Mohaghegh Ardabili, Ardabil, Iran.

PAPER INFO

Paper history:
Received: Apr. 29, 2025
Revised: May, 31, 2025
Accepted: Oct. 01, 2025
Available Online: Dec. 30, 2025

Keywords:
Renewable Energies
Optimization
Robot
Simulation
Agriculture

ABSTRACT

Contemporary agriculture faces a dual challenge: meeting the food demands of a growing population while mitigating its environmental footprint. Conventional farming machinery, despite its vital role in boosting productivity, contributes to irreversible ecological damage through greenhouse gas emissions and soil compaction. In this context, electric agricultural robots emerge as a transformative solution, offering three key advantages: eliminating direct pollutant emissions, significantly reducing carbon footprints, and optimizing energy consumption. These advanced technologies enable precise, controlled operations that maintain soil structure and microbial ecosystems while ensuring long-term agricultural sustainability. Critical operational parameters such as working speed and depth have been identified as decisive factors in energy efficiency—their optimization could mark a turning point in harmonizing high yields with sustainable practices. This technological shift not only addresses current environmental challenges but also establishes a new paradigm for agricultural mechanization, charting a sustainable future for the industry. A robot pulling a rotivator was simulated in MATLAB version R2022b software, and all the forces applied to the robot and rotivator were applied. To get the answer closer to reality, the soil was considered variable. The goal is to find the best working mode of the robot that has the lowest energy consumption. The highest amount of energy consumption was observed at high speeds (10 km/h). By increasing the depth of the rake from 5 to 10 cm, energy consumption increased by 19% on average. The largest amount of energy loss was included in the pseudo-made set of tires. About 40 to 45 percent of the total losses in the simulation set are assigned to tires. The findings showed that the depth of work has a greater effect on losses than the speed of movement. The intensity of the operation significantly affects the battery losses. In the lightest mode, the battery loss was 1.2 Wh/km and in the heaviest mode, the battery loss increased to 6.1 Wh/km. In general, it can be concluded that the robot should be used at a low depth and at low speeds in order to have the lowest amount of energy consumption. Less use of energy and renewable resources is essential to achieve sustainable development.

1. Introduction

The global population is projected to reach 9.7 billion by 2050 (Bongaarts, 2020). This demographic surge necessitates significant advancements in agricultural productivity (Khodkam et al., 2025). It should be emphasized that the agricultural sector contributes substantially to greenhouse gas emissions and environmental degradation, warranting immediate mitigation strategies to reduce its ecological footprint (Khodkam et al., 2024; Bagheri & Khodkam, 2025). Based on available data, researchers estimate that the agricultural sector accounts for approximately 15% of total global greenhouse gas emissions (Gerber et al., 2013). This compelling evidence necessitates the development of strategies to optimize farming operations (particularly to reduce carbon emissions from agricultural machinery). Biofuel blending has been proposed as one mitigation approach for reducing agricultural GHG emissions (Lovarelli & Bacenetti, 2019). While effective, this method requires further modifications to achieve significant emission reductions. The electrification of agricultural machinery presents a promising pathway to simultaneously enhance productivity and environmental sustainability.

The concept of smart agriculture, which has recently gained significant attention, involves utilizing technologies such as remote control, artificial intelligence, and robotics to enhance farming operation efficiency (Ragazou et al., 2022). The electrification of agricultural machinery and the adoption of renewable energy sources have been identified as fundamental steps toward large-scale implementation of smart farming (Khodkam et al., 2024). In this regard,

*Corresponding author's email: gaderbalkipor@gmail.com

Please cite this article as: Balkipor, G., & Abbaspour Gilandeh, Y., (2025). Simulation and Optimization of Wheeled Electric Robots and its Effects to Achieve Sustainable Development. *Biosystems Engineering & Sustainable Technologies (BEST), 2*(1), 11-19. https://doi.org/10.22084/best.2025.30904.1008

recent studies have increasingly focused on renewable energy applications in agriculture (Hernandez-Escobedo et al., 2022; Kheiralipour et al., 2024). However, the high energy demand in agricultural operations poses significant challenges to machinery electrification (Lajunen et al., 2023), with battery limitations, slow charging rates, and a lack of charging infrastructure impeding progress toward these objectives (Malik & Kohli, 2020). Depending on farm conditions, renewable-powered operations can reduce carbon emissions by up to 70% (Lagnelöv et al., 2023). These emissions endanger human health and contribute to ecosystem alterations (Khodkam, 2024). When fossil fuels power electric machinery charging, carbon reduction benefits become marginal. Complete carbon neutrality requires renewable-sourced electricity generation. This approach fully complies with net-zero principles, safeguarding future generations' interests.

However, numerous challenges hinder the widespread implementation of electric agricultural machinery. Currently, commercially available electric machinery is only suitable for operations in limited sections of farmland (Beltrami et al., 2021). As a potential solution, the use of small robotic systems has been proposed to overcome the limitations of electric farm equipment (Lagnelöv et al., 2021). Two critical approaches for enhancing the usability of autonomous charging robots include on-site renewable energy generation and storage integration (Olkkonen et al., 2023). The incorporation of Photovoltaic (PV) modules with agricultural robots represents a significant performance-enhancing solution (Gorjian et al., 2023). Nevertheless, optimal robot design remains heavily dependent on specific operational environments (Roshanianfard et al., 2020). Notably, replacing conventional tractors with lightweight machinery can effectively mitigate soil compaction issues (Lagnelöv et al., 2023). Heavy tractor operations typically increase soil compaction and reduce water retention capacity, ultimately leading to diminished crop yields.

Robot simulation and performance optimization for energy efficiency represent essential requirements for power supply management. To address this need, the present study proposes a novel modeling approach for an electric wheeled robot (battery-powered) with dimensions comparable to ground vehicles. The simulation model incorporates propulsion systems, tire-soil interaction models, and implementation frameworks. The tire-soil interaction model accounts for deformable terrain characteristics. For simulation model development, an electric robot performing rotavator towing operations was utilized.

Affordable, safe, sustainable, and modern energy constitutes a key sustainable development goal (Hadryjańska, 2021). Ensuring energy security, mitigating climate change impacts, and enhancing economic welfare and development are essential for energy utilization (Elahi et al, 2022). The energy sector plays a pivotal role in implementing sustainable development concepts. Numerous researchers emphasize that this requires a fundamental restructuring of the global economy (Zakari & Oluwaseyi Musibau, 2024).

Despite increasing adoption of electric agricultural robotics, persistent limitations in energy efficiency and tire-soil interaction dynamics hinder their widespread implementation. Current systems face three fundamental challenges: inadequate battery performance, suboptimal power management, and insufficient integration of terrain-specific soil mechanics. This study addresses these gaps by developing a comprehensive simulation framework that rigorously models battery-powered robots, explicitly incorporating tire-soil interaction mechanics. research aims to quantify energy consumption patterns across operational scenarios, analyze tire design impacts on soil compaction and traction efficiency, and establish optimal design parameters for enhanced energy performance. The resulting validated simulation platform enables predictive optimization of robotic systems for minimal energy consumption while maintaining operational effectiveness across diverse terrains. By bridging critical gaps between theoretical models and field applications, this work advances the development of next-generation agricultural robots that simultaneously achieve operational efficiency and environmental sustainability targets through physics-based design methodologies and empirically validated implementation frameworks.

1.1 Tire-soil interaction models

The primary objective of tire-soil interaction modeling is to accurately calculate tire force and torque characteristics on deformable terrain (Dasch et al., 2012). Assessing tire passage effects on soil properties, including surface profile and compaction, holds particular significance in agricultural studies. Tire-soil interaction models can be classified into three categories: empirical, semi-empirical, and physics-based models (Taheri et al., 2015). While empirical models initially gained widespread popularity, physics-based approaches have recently attracted greater research attention.

Empirical models are developed through three key stages: (1) Identification of the most influential measurable factors affecting vehicle (tractor/robot) performance, (2) Wheel mobility tests, and (3) Application of curve-fitting methods to establish trends in measured data. A widely used empirical parameter is the vehicle mobility number (for tractors/robots), which is a function of soil strength, tire load, and tire geometry (Schreiber & Kutzbach, 2008).

Semi-empirical models, unlike purely empirical approaches, incorporate analytical methods alongside experimental measurements and empirical formulas to compute tire-soil interactions. While various semi-empirical models have been developed over the years, the most widely adopted is the Bekker-Wong formulation (Wong & Reece, 1967). Several modifications have been implemented to enhance the accuracy of the Bekker-Wong model, the most significant being the incorporation of soil moisture variation effects (Sandu et al., 2005).

The Bekker-Wong model has been utilized for diverse applications in previous studies. One research effort employed this model to analyze tractor rollover on sloped terrains (Holtz et al., 2014), while another investigation applied it to study Soil Contact Mechanics (SCM) of tractor tires (Krenn & Gibbesch, 2011). Recently, a novel approach combining the Bekker-Wong equations with neural networks has been proposed to enhance the tire-soil interaction model, enabling better characterization of the dynamic nature of soil reaction forces (Karpman et al., 2023).

Physics-based models employ fundamental physical principles and analytical methods to represent tire structures, terrain, and their interactions (Taheri et al., 2015). While these approaches enable high-fidelity tire-soil contact simulation, they demand substantial computational resources. Conventional models were typically two-dimensional (Fervers, 2004), whereas modern implementations utilize three-dimensional formulations to enhance computational capability (Serban et al., 2019). A prevalent physics-based method involves finite element modeling of both tires and soil particles (Recuero et al., 2017).

1.2. Simulation of agricultural machinery

Simulation results of an electric tractor evaluating different charging systems revealed that electric tractors require significantly more time for transportation and recharging compared to their diesel counterparts. Furthermore, the study demonstrated that employing smaller charging tractors presents an effective solution to address battery capacity and recharging challenges (Lagnelöv et al., 2021). When compared to conventional internal combustion engine (ICE) tractors, electric tractors exhibit lower annual operating costs but higher initial capital investments. Notably, electric tractors (when charged with clean electricity) can substantially reduce greenhouse gas emissions relative to diesel-powered tractors (Lagnelöv et al., 2021).

This study investigates tire-soil interaction on deformable terrain by simulating an electric wheeled agricultural robot, incorporating an electric propulsion system and a dynamic model of the robot's towed implement to calculate optimal energy consumption. This approach enables energy usage minimization while maximizing operational efficiency and minimizing environmental impacts. The primary objective is to identify optimal robotic operating conditions for energy reduction. Currently, in Iran, fossil fuels remain the primary electricity source; however, a transition toward renewable energy is emerging. In both scenarios, minimizing energy consumption is essential to achieve sustainable development goals.

A two-dimensional simulation model of an electric wheeled agricultural robot towing a rotavator was developed in MATLAB/Simulink (R2022b version). A fixed gear ratio was implemented. The main components of the simulation model include: (1) propulsion system model, (2) tire-soil interaction model, (3) robot motion equations, (4) rotavator dynamics, and (5) control algorithm.

2. Method

2.1. Simulation parameters

The propulsion model used in this study consists of two main components: an efficiency-map-based motor model and a resistive battery model. This modeling is adapted from a similar approach to the plug-in electric bus system developed in previous studies (Kivekäs et al., 2019). The robot parameters are listed in Table 1, while the towed rotavator specifications are documented in Table 2. All computational analyses were performed based on these numerical parameters. The center of gravity height was set at 0.6 meters. The battery was configured to operate at 48 volts with an approximate energy capacity of 17 kWh. Three tine depths (5, 10, and 15 cm) were simulated. Four operating speeds (4, 6, 8, and 10 km/h) were defined.

2.2. Tire-soil interaction model

Given the relatively small tire size of the simulated robot, the tire model was assumed to be rigid in the simulation. The robot wheels have a diameter of 0.6 meters, while the rotavator wheels measure 0.5 meters in diameter. The rigid wheel implementation employed the classical and widely used model developed by Wong and Reece (1967). Given the small diameter of both the robot's wheels and the rotator wheels, the assumption of rigid tires is dynamically justified. At such small scales, tire deformation has a negligible effect

Table 1. Robot parameters

Parameter	Size
Distance between two axles (m)	1.30
Machine width (m)	1.20
Weight (kg)	500
Maximum power (kw)	10
Maximum torque (Nm)	140
Maximum speed (rpm)	3000
Final drive ratio	17.9
Final drive efficiency (%)	98
Battery capacity (Ah)	360
Battery energy capacity (kwh)	17.1
Nominal battery voltage (v)	48.1
Tire diameter (m)	0.6
Tire width (m)	0.2
Device power demand assistance (w)	200

Table 2. Rotivator parameters

Parameter	Size
Length (m)	2.0
Width (m)	1.30
Mass (kg)	200
Number of crochet rows (-)	2
Number of hooks per row (-)	5
Hook length (m)	0.25
Hook width (m)	0.02
Tire diameter (m)	0.5
Tire width (m)	0.17

on the system's overall behavior. The shear stress distribution was calculated using the relationship defined by Janosi and Hanamoto (1961):

$$\tau(\theta) = \tau_{max}\,(1 - e^{\frac{-j}{k}}) \tag{1}$$

where τmax is the maximum shear stress, j represents soil shear displacement, k denotes the shear deformation modulus, and θ describes the angular position of the tire. As illustrated in Fig. 1, θ equals zero at the tire bottom contact point and increases counterclockwise during rotation (Wong & Reece, 1967).

$$s_{du} = \frac{\omega R - \upsilon_{\omega}}{\upsilon_{\omega}} \tag{2}$$

The maximum shear stress is calculated based on equation 2:

$$\tau_{max} = c + \sigma(\theta)\tan(\varphi) \tag{3}$$

where c is the soil cohesion, σ is the normal stress, and φ is the angle of internal shear resistance of the soil. The shear displacement is calculated as follows (Wong & Reece, 1967):

$$j+(\theta) = R[(\theta_e - \theta) - (1 - s_d)(\sin(\theta_e) - \sin(\theta))] \tag{4}$$

Where θ is the wheel entry angle, as seen in Fig. 3.

Fig. 2 shows a schematic of the forces acting on the robot and their points of application. The points of application of the tangential (Fτ) and normal (Fσ) forces of the tire can be different at the contact point. In this robot, both the front and rear axles provide traction. The soil behind the tires, which is lower in height than in front of the tires, indicates soil compaction by the tires.

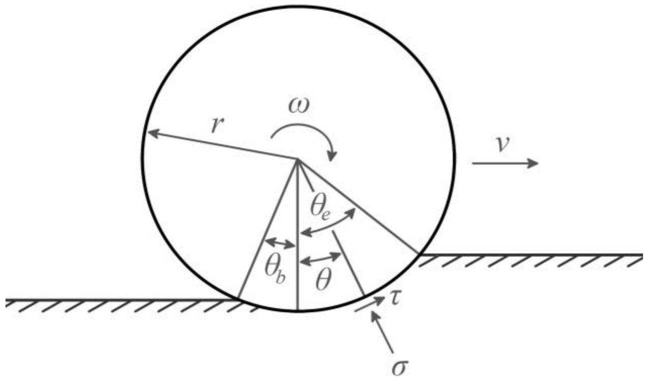

Fig. 1. Normal stress σ and tangential stress τ are applied to a rigid wheel on deformable soil

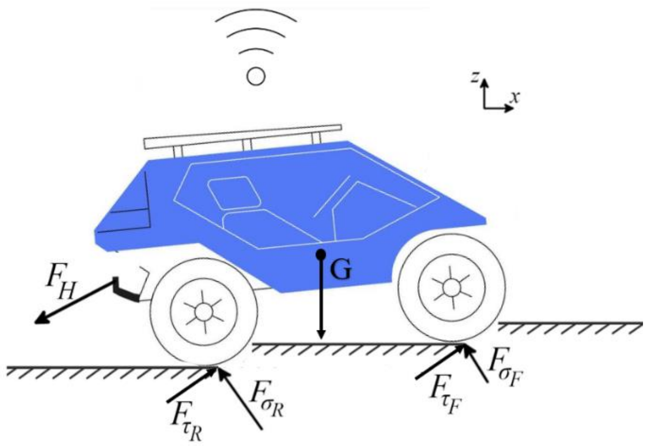

Fig. 2. Schematic of the forces affecting the robot

The longitudinal and vertical forces of the towed implement depend on multiple factors, including dimensions, operating speed, working depth, orientation angle, as well as soil density and internal friction. Fig. 3 illustrates the soil deformation model used in calculations, where β represents the soil shear angle and δ denotes the blade angle.

3. Results

3.1. Success matrices and energy consumption changes

As anticipated, peak energy consumption occurred during operational cycles with maximum tine depth and highest operating speed. Conversely, minimal energy usage was achieved at a 5 cm tine depth with speeds of either 6 or 8 km/h. These results highlight the critical importance of optimal speed selection for energy efficiency maximization and consequent operational range extension. Figure 4

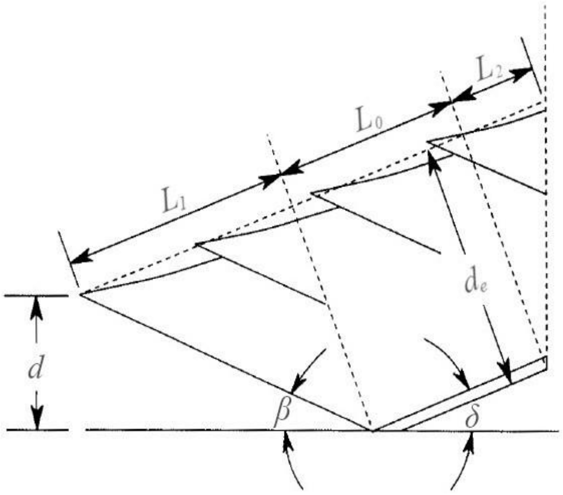

Fig. 3. A part of the soil that is operated by a rake (Srivastava et al., 1993)

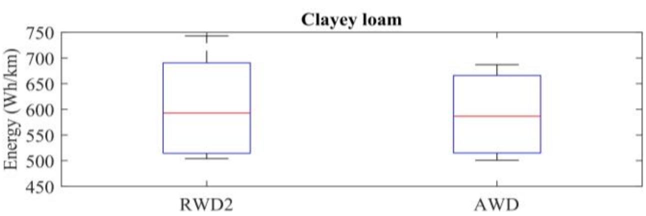

Fig. 4. Distribution of energy consumption

presents the energy consumption distribution. Notably, while the robot was equipped with regenerative braking capability, high resistive forces typically rendered braking unnecessary. Regenerative braking was only employed in sandy soil conditions with a 5 cm blade depth.

Fig. 5 demonstrates the influence of various operational parameters. In clay-loam soil, increasing tine depth from 5 to 10 cm raised energy consumption by an average of 19%, while deeper penetration to 15 cm resulted in a 33.9% energy increase. Notably, the effect of travel speed shows significant dependence on working depth: accelerating from 4 to 10 km/h at 5 cm depth increased consumption by only 3.2%, whereas the same speed increase at 15 cm depth caused a 10.8% surge. These findings reveal that implementing configuration (depth) has a greater impact on energy demand than robot speed.

Collectively, these results demonstrate the significant influence of soil properties, robot configuration, and propulsion system design on both energy consumption and operational range. Furthermore, the complete coverage operation achievable with a single charge confirms the system's capability to maintain high work rates. Given the emerging nature of electric agricultural machinery, direct energy consumption comparisons with these results are

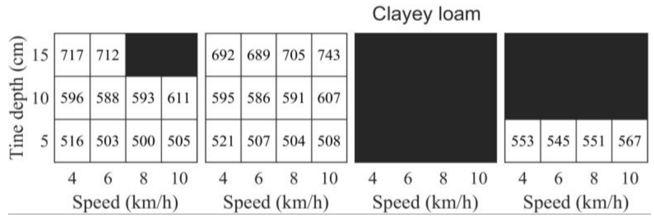

Fig. 5. Distribution of energy consumption

currently limited. In a related study, energy consumption for an 8.6-ton electric tractor during tillage operations was recorded between 33-49 kWh per hectare, depending on workload (Lajunen, 2022). Comparatively, the electric agricultural robot demonstrates approximately one-tenth the energy consumption of its electric tractor counterpart.

3.2. Performance comparison with light workload

Fig. 6 presents the energy loss analysis in clay-loam soil under 5 cm tine depth operation at the target speed of 4 km/h. Tires emerged as the primary energy dissipation source in this operational cycle. Tire-related losses comprised both slip losses and rolling resistance. The obtained percentages exceeded those simulated for a 10-ton electric tractor during tillage operations (Lajunen et al., 2023). Their results indicated that tire losses accounted for 40-45% of total energy dissipation under light workload conditions.

Excessive slip in the front tires induced deeper soil penetration. Consequently, the rear tires also operated at greater depths due to the ruts formed by the front tires. Rolling resistance increased proportionally with the deeper sinkage of the drive wheels. Fig. 7 illustrates the interrelationship between tire penetration depth, slip ratio, and rolling

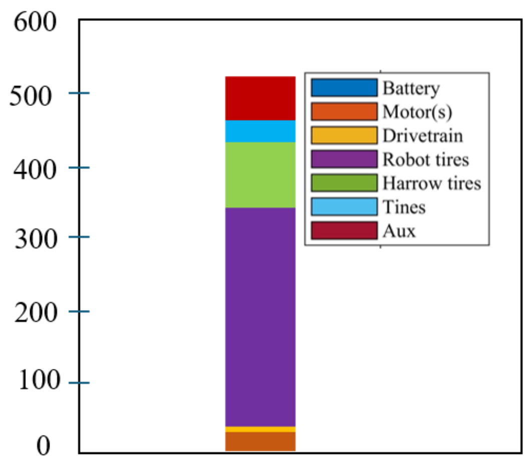

Fig. 6. Energy losses in clay loam soil by source

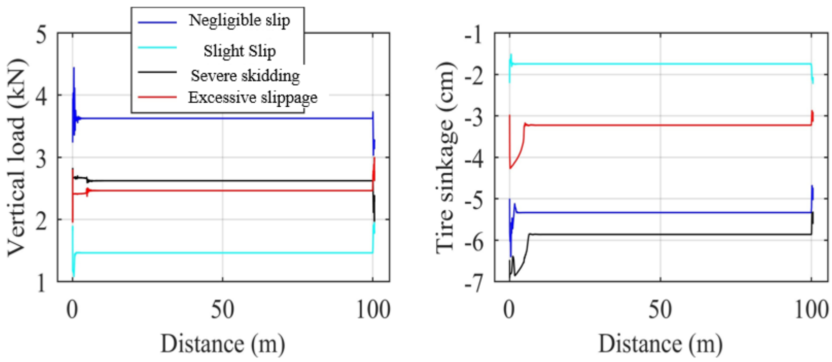

Fig. 7. Vertical loads on the axles and tire indentation.

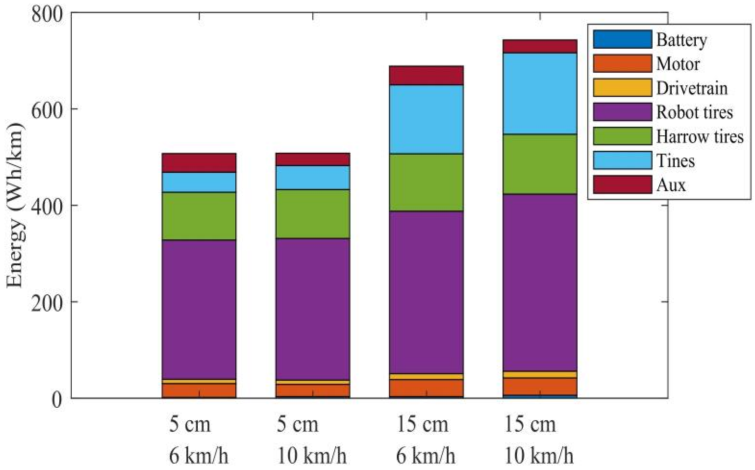

Fig. 8. Distribution of energy loss in different depths.

resistance. The front-row tines penetrated deeper into the soil compared to the rear-row tines, attributable to the greater sinkage of the robot's rear tires relative to the rotavator's tires.

3.3. The impact of the operating cycle on energy consumption

Fig. 8 displays the energy dissipation distribution in clay-loam soil, revealing that tine losses account for the most substantial increase in energy consumption. Comparative analysis between the 5 cm tine depth at 6 km/h operation and the 15 cm depth at 10 km/h cycle shows a remarkable 305% surge in tine-related energy losses. Furthermore, rotavator tire losses increased by 25% due to greater soil penetration during intensive operations.

Alternatively, increasing working depth from 5 cm to 15 cm at a constant 6 km/h speed elevated tine losses by 243%. These findings conclusively demonstrate that working depth exerts a greater influence on energy dissipation than operational speed. Operation intensity significantly impacts battery losses. Under light-duty conditions (5 cm tine depth at target 6 km/h speed), battery losses measured 1.2 Wh/km. During heavy-duty operation (15 cm depth at 10 km/h), battery losses escalated to 6.1 Wh/km.

4. Conclusions

The growing global population will intensify agricultural demands. Conventional farming practices contribute significantly to greenhouse gas emissions and environmental degradation, necessitating transformative changes in agricultural operations. This study proposes the adoption of electric agricultural robots as a sustainable alternative. We present a novel simulation model of an electric agricultural robot performing rotavator towing operations. The developed model integrates: (1) an electric propulsion system, (2) a tire-soil interaction model accounting for deformable terrain, and (3) rotavator dynamics. Results demonstrate that optimal propulsion configuration is highly dependent on workload intensity and soil type characteristics.

Identifying optimal operational parameters is essential for sustainable development, ensuring effective fulfillment of current needs while preserving resources for future generations. Electric robots generate substantially lower emissions compared to conventional tractors, with near-zero emissions achievable when powered by renewable energy sources. Affordable and clean energy represents a fundamental sustainable development goal, enabling comprehensive fulfillment of present requirements while safeguarding the interests of future generations.

Speed is a critical parameter influencing energy consumption. Maximum energy consumption occurred at the highest travel speed and deepest tine depth. Conversely, the lowest energy consumption was achieved at a tine depth of 5 cm and speeds of either 6 or 8 km/h. The results demonstrated that implementing configuration (depth) has a greater impact on energy consumption than robot speed. Increasing the tine depth from 5 cm to 10 cm led to an average 19% rise in energy demand.

Tires were the main source of energy loss during operation. Results indicated tire-related losses accounted for 40-45% of total energy loss under light load conditions. Excessive tire slippage induced greater soil penetration depth, consequently causing rear tires to operate at deeper levels due to rut formation from front tire passage. This phenomenon led to measurable increases in rolling resistance. Notably, front-row tines exhibited deeper soil penetration compared to rear-row tines, attributable to the more pronounced sinkage of the robot's rear tires in the soil profile.

The highest energy losses were attributed to the tillage tines. Under maximum operational intensity (15 cm depth at 10 km/h speed), energy consumption increased by 305%, with rotavator tire losses simultaneously rising by 25%. Comparatively, increasing tine working depth from 5 cm to 15 cm at a constant 6 km/h speed resulted in a 243% escalation in tine-related energy dissipation. Operational intensity significantly impacts battery energy losses. Under minimal-load conditions (5 cm tine depth at target 6 km/h speed), battery dissipation measured 1.2 Wh/km. During peak-load operation (15 cm depth at 10 km/h), battery losses increased to 6.1 Wh/km, representing a 408% increase in energy demand. In summary, optimal operational efficiency is achieved when employing the robot under light-duty conditions (5 cm working depth) at reduced speeds, maximizing energy efficiency while minimizing power consumption. Furthermore, transitioning to renewable energy sources is essential for greenhouse gas mitigation, thereby enabling sustainable energy implementation.

To accelerate the adoption of electric agricultural robots and maximize their environmental benefits, policymakers should implement a three-pronged strategy: First, establish financial incentive programs including tax credits, subsidies, and low-interest loans to offset the higher upfront costs of electric robotic systems, particularly for small and medium-sized farms. Second, develop infrastructure support initiatives focusing on rural charging stations powered by renewable energy and training programs for farmers and technicians. Third, implement regulatory measures such as phased emission standards for agricultural equipment and carbon pricing mechanisms that account for the full lifecycle emissions of farming operations. These policies should be integrated with existing agricultural modernization and climate action plans, creating synergy with renewable energy deployment targets. A successful policy framework must balance technological innovation with socioeconomic considerations, ensuring equitable access across farm sizes and regions while driving the transition toward sustainable intensification of agriculture. International collaboration will be crucial to harmonize standards, share best practices, and create global markets for these transformative technologies.

From a long-term perspective, sustainable energy policies should be designed to:

- Substituting renewable energies
- Promoting equitable greenhouse gas emissions
- Gradual reduction of energy consumption
- Reducing the consequences of the negative impact of energy on the environment
- More efficient and less harmful energy production, transmission, and distribution.

References

Lagnelöv, O., Dhillon, S., Larsson, G., Nilsson, D., Larsolle, A., & Hansson, P. A. (2021). Cost analysis of autonomous battery electric field tractors in agriculture. *biosystems engineering, 204*(1), 358-376.

Bagheri, E., & Khodkam, H. (2025). Smart Farming: How Drones Are Transforming the Future of Food Production?. *Biosystems Engineering & Sustainable Technologies (BEST), 1*(1), 45-61. https://doi.org/10.22084/best.2025.30490.1004

Beltrami, D., Iora, P., Tribioli, L., & Uberti, S. (2021). Electrification of compact off-highway vehicles—overview of the current state of the art and trends. Energies, *14*(17), 5565. https://doi.org/10.3390/en14175565

Dasch, J. M., & Gorish, D. J. (2013). The TARDEC story: Sixty-five years of innovation 1946-2010. Government Printing Office.

Elahi, E., Khalid, Z., & Zhang, Z. (2022). Understanding farmers' intention and willingness to install renewable energy technology: A solution to reduce the environmental emissions of agriculture. *Applied Energy, 309*(1), 118459. https://doi.org/10.1016/j.apenergy.2021.118459

Fervers, C. W. (2004). Improved FEM simulation model for tire–soil interaction. *Journal of Terramechanics, 41*(2-3), 87-100. https://doi.org/10.1016/j.jterra.2004.02.012

Gerber, P. J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., & Tempio, G. (2013). Tackling climate change through livestock: a global assessment of emissions and mitigation opportunities (pp. xxi+-115). http://www.fao.org/docrep/018/i3437e/i3437e00.htm

Gorjian, S., Ebadi, H., Trommsdorff, M., Sharon, H., Demant, M., & Schindele, S. (2021). The advent of modern solar-powered electric agricultural machinery: A solution for sustainable farm operations. *Journal of Cleaner Production, 292*(1), 126030. https://doi.org/10.1016/j.jclepro.2021.126030

Graczyk, A. (2017). Wskaźniki zrównoważonego rozwoju energetyki. *Optimum. Economic Studies, 88*(4), 53-68.

Hadryjańska, B. (2021). Droga do zrównoważonego rozwoju w Polsce w świetle założeń Agendy 2030. Difin.

Hernández-Escobedo, Q., Muñoz-Rodríguez, D., Vargas-Casillas, A., Juárez López, J. M., Aparicio-Martínez, P., Martínez-Jiménez, M. P., & Perea-Moreno, A. J. (2022). Renewable Energies in the Agricultural Sector: A Perspective Analysis of the Last Three Years. *Energies, 16*(1), 345. https://doi.org/10.3390/en16010345

Holtz, D., Singh, A., & Megiveron, M. G. (2014, August). Tire-Soil Modeling for Vehicle Rollover Over Sloped Compressible Terrains. *In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (Vol. 46346, p. V003T01A029). American Society of Mechanical Engineers*. https://doi.org/10.1115/DETC2014-35662

Janosi, Z. (1961). The analytical determination of drawbar pull as a function of slip for tracked vehicles in deformable soils. *In International Society for Terrain-Vehicle Systems, 1st Int. Conf. (Vol. 707)*. https://doi.org/10.13031/epam.2013

Karpman, E., Kövecses, J., & Teichmann, M. (2023). Terramechanics models augmented by machine learning representations. *Journal of Terramechanics, 107*(1), 75-89. https://doi.org/10.1016/j.jterra.2023.03.002

Kheiralipour, K., Khoobbakht, M., & Karimi, M. (2024). Effect of biodiesel on the environmental impacts of diesel mechanical power generation by life cycle assessment. *Energy, 289*(129948). https://doi.org/10.1016/j.energy.2023.129948

Khodkam H. (2025). A review of the effective factors involved in the production of biogas from biomass waste. *Biosystems Engineering and Renewable Energies, 1*(1), 203-213, 51-58. https://doi.org/10.22069/bere.2025.23043.1011

Khodkam, H. (2024). The best approach to build a solar power plant to increase efficiency and location in several climatic climates of Iran using AHP software. *Journal of Renewable and New Energy, 11*(1), 148-157.10.22034 / jrenew 2023.185722

Khodkam, H., Pourdarbani, R., Ghaebi, H., & Hernandez-Hernandez, M. (2024). Investigating the Environmental Impacts of Different Approaches of Agricultural Waste Management Using AHP Technique. *Acta Technologica Agriculturae, 27*(4), 242-250. DOI: 10.2478/ata-2024-0032

Kivekäs, K., Lajunen, A., Baldi, F., Vepsäläinen, J., & Tammi, K. (2019). Reducing the energy consumption of electric buses with design choices and predictive driving. *IEEE Transactions on Vehicular Technology, 68*(12), 11409-11419.10.1109 /TVT.2019.2936772

Krenn, R., & Gibbesch, A. (2011). Soft soil contact modeling technique for multi-body system simulation. *Trends in computational contact mechanics, 1*(1), 135-155.

Lagnelöv, O., Larsson, G., Larsolle, A., & Hansson, P. A. (2021). Life cycle assessment of autonomous electric field tractors in Swedish agriculture. *Sustainability, 13*(20), 11285. https://doi.org/10.3390/su132011285

Lagnelöv, O., Larsson, G., Larsolle, A., & Hansson, P. A. (2023). Impact of lowered vehicle weight of electric autonomous tractors in a systems perspective. https://doi.org/10.1016/j.atech.2022.100156

Lajunen, A. (2022). Simulation of energy efficiency and performance of electrified powertrains in agricultural tractors. *IEEE Vehicle Power and Propulsion Conference (VPPC)* (pp. 1-6). IEEE.10.1109 / VPPC55846.2022.10003394

Lajunen, A., Kivekäs, K., Freyermuth, V., Vijayagopal, R., & Kim, N. (2023, June). Simulation of alternative powertrains in agricultural tractors. *In Proceedings of the 36th International Electric Vehicle Symposium and Exhibition (EVS36), Sacramento, CA, USA.* (pp. 11-14).

Lovarelli, D., & Bacenetti, J. (2019). Exhaust gases emissions from agricultural tractors: State of the art and future perspectives for machinery operators. *Biosystems engineering, 186*(1), 204-213. https://doi.org/10.1016/j.biosystemseng.2019.07.011

Malik, A., & Kohli, S. (2020). Electric tractors: Survey of challenges and opportunities in India. *Materials Today: Proceedings, 28*(1), 2318-2324. https://doi.org/10.1016/j.matpr.2020.04.585

Olkkonen, V., Lind, A., Rosenberg, E., & Kvalbein, L. (2023). Electrification of the agricultural sector in Norway in an effort to phase out fossil fuel consumption. *Energy, 276*(1), 127543. https://doi.org/10.1016/j.energy.2023.127543

Ragazou, K., Garefalakis, A., Zafeiriou, E., & Passas, I. (2022). Agriculture 5.0: A new strategic management mode for a cut cost and an energy-efficient agriculture sector. *Energies, 15*(9), 3113. https://doi.org/10.3390/en15093113

Recuero, A., Serban, R., Peterson, B., Sugiyama, H., Jayakumar, P., & Negrut, D. (2017). A high-fidelity approach for vehicle mobility simulation: Nonlinear finite element tires operating on granular material. *Journal of Terramechanics, 72*(1), 39-54. https://doi.org/10.1016/j.jterra.2017.04.002

Roshanianfard, A., Noguchi, N., Okamoto, H., & Ishii, K. (2020). A review of autonomous agricultural vehicles (The experience of Hokkaido University). *Journal of Terramechanics, 91*(1), 155-183.

Sandu, C., Sandu, A., & Li, L. (2005). Stochastic modeling of terrain profiles and soil parameters. *SAE transactions, 4*(1), 211-220. https://www.jstor.org/stable/44658105

Schreiber, M., & Kutzbach, H. D. (2008). Influence of soil and tire parameters on traction. *Research in Agricultural Engineering, 54*(2), 43-49.

Serban, R., Negrut, D., Recuero, A., & Jayakumar, P. (2019). An integrated framework for high-performance, high-fidelity simulation of ground vehicle-tyre-terrain interaction. *International journal of vehicle performance,* *5*(3), 233-259. https://doi.org/10.1504/IJVP.2019.100698

Srivastava, A. K., Goering, C. E., Rohrbach, R. P., & Buckmaster, D. R. (1993). Engineering principles of agricultural machines.

Taheri, S., Sandu, C., Taheri, S., Pinto, E., & Gorsich, D. (2015). A technical survey on Terramechanics models for tire–terrain interaction used in modeling and simulation of wheeled vehicles. *Journal of Terramechanics, 57*(1), 1-22. https://doi.org/10.1016/j.jterra.2014.08.003

Tarighi, J., Khodkam, H., & Ghorbani, A. (2024). A review of optimizing biogas production through pretreatment and pollution reduction. *Journal of Renewable and New Energy, 11*(2), 203-213.10.22034 /jrenew 2024.200573

Wong, J. Y., & Reece, A. R. (1967). Prediction of rigid wheel performance based on the analysis of soil-wheel stresses, part I. Performance of driven rigid wheels. *Journal of Terramechanics, 4*(1), 81-98. https://doi.org/10.1016/0022-4898(67)90105-X

Zakari, A., & Oluwaseyi Musibau, H. (2024). Sustainable economic development in OECD countries: Does energy security matter?. *Sustainable Development, 32*(1), 1337-1353. https://doi.org/10.1002/sd.2668