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Efficient Energy Management System using Honey Badger Algorithm for Smart Agriculture

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Abstract: *Today, optimization is crucial to solving energy crises, especially in smart homes. However, the optimization-based methods for energy management in smart agriculture available globally need further improvement, which motivates this study. To resolve the problem, an efficient scheduling farm energy management system is required. Therefore, this study proposes a Farm Energy Management System (FEMS) for smart agriculture by adopting a honey-badger optimization algorithm. In the proposed system, a multi-objective optimization problem is formulated to find the best solutions for achieving the set of objectives, such as electricity cost, load minimization and peak-to-average ratio minimization, while considering the farmers' comfort. The proposed system considers commercialized agriculture with the integration of Renewable Energy Resources (RES). Also, the proposed system minimizes both load consumption and electricity costs via the scheduling of farm appliances in response to Real-Time Pricing (RTP) and Time-of-Use (ToU) pricing schemes in the electricity market. Extensive experiments are carried out in MATLAB 2018A to determine the efficacy of the proposed system. The proposed FEMS consists of sixteen farm appliances with their respective power ratings, inclusive of RES. The simulation results showed that a system without FEMS has a high electricity cost of 50.69% as compared to 43.04% for FEMS without RES and 6.27% for FEMS with RES when considering the ToU market price. For RTP market price, a system without FEMS has an electricity cost of 42.30%, as compared to 30.64% for FEMS without RES and 27.24% for FEMS with RES. Besides, the maximum load consumption for a system without FEMS is 246.80 kW, as compared to 151.40 kW for FEMS without RES and 18.85 kW for FEMS with RES when considering the ToU market price. Also, for the RTP market price, the maximum load consumption for a system without FEMS is 246.80 kW, as compared to 186.40 kW for FEMS without RES and 90.68 kW for FEMS with RES. The significance of the study is to propose a conceptualized FEMS based on the honey badger optimization algorithm. The proposed system provides scheduling of farm appliances that alleviates the burden of the electricity grid and is cost-effective for large and small-scale farmers.*

Keywords: *Agricultural Appliances, Farm Energy Management System, Honey Badger Algorithm, Renewable Energy Resources, Scheduling, Smart Agriculture.*

1. INTRODUCTION

Today, the field of numeric optimization has been used to solve optimization problems in several applications [1]. It involves minimizing or maximizing evaluation measures, known as the objective function. Numerical optimization is based on the following techniques: linear programming, integer programming, quadratic programming, non-linear programming, dynamic programming, stochastic optimization, combinatorial programming, and the evolution algorithm. Moreover, these optimization techniques are employed to find the optimal solutions (i.e., the best solution) for the systems while considering the values that minimize or maximize the output. Although linear, convex, low-dimensional, and differentiable problems respond well to deterministic methods in either systems that use gradients or those that do not. These methods, however, become less essential when dealing with optimization issues that include non-linear, non-convex, complex, high-dimensional, non-differentiable, discrete search space, and nondeterministic polynomial time (NP) hard issues [2]. Stochastic approaches, which include random operators, random searches, and trial-and-error procedures, have begun to gain popularity and are vital in optimization applications. Moreover, stochastic approaches as meta-heuristic optimization algorithms have grown to be very well-liked and widely used [2]. The optimization process can be a single-objective optimization problem or a multi-objective optimization problem [3]. A single optimization problem involves finding the best solution for a specific metric or condition, e.g., the execution time for determining the performance of a system. Contrarily, the multi-objective optimization problem finds the best solution involving two or more objective functions for multiple criteria decision-making [4]. These optimization problems comprise objective functions, decision variables, and constraints. The optimization problems are measured based on decision variables and constraints for producing the objective function that is to be optimized [2]. With the emergence of Science, Technology, Engineering, and Mathematics (STEM), the importance of optimization in different areas of human endeavors has become much clearer. In the energy sector, optimization has been critical in addressing the issue of the energy crisis [5]. Here, energy management strategies have been proposed based on deterministic and heuristic optimization approaches [6]. Home energy management is one of the energy management strategies, in which household appliances are scheduled to minimize energy consumption and load while maximizing user comfort [7]. Also, energy management strategies for the energy generation side, i.e., microgrids, have been proposed. The optimization approach helps to determine the degree of fault-tolerance in microgrid systems [8]. Furthermore, Renewable Energy Resources (RES) [9] have been integrated into the energy management system for balancing energy demand and supply. The aim is to allow grid with insufficient energy to meet household power demands [10]. In the manufacturing sector, optimization has been applied for energy control [11]. Also, the problem of robotic path planning has been addressed via optimization [12]. Similarly, optimization is employed to reduce energy use in a pharmaceutical process while preserving product quality and adhering to operational restrictions [13]. In the healthcare sector, how to locate collection centres, assigning blood donors to centres, maintain inventory levels in the primary blood centre, account for blood shortage and deterioration issues, and implementing queuing systems in collection centres during a planning period are multiple challenges. To this end, meta-heuristic optimization is deployed to reduce the system's waiting time, which increases donor satisfaction while minimizing overall expenditures [14]. Also, optimization is used for vaccine supply chain solutions where challenges in the public immunization program are met [15]. In the agricultural sector, optimization has been used to solve river basin management and supply chain problems [16]. Although surveys by [17,18] presented three development modes of smart agriculture and Internet of things (IoT) while discussing the security challenges and countermeasures. However, energy management for agricultural appliances is not considered. To this end, we are motivated to employ a honey badger optimization algorithm for achieving energy management in smart agriculture. In this study, the cost-effective Farm Energy Management System (FEMS) and a Peak-to-Average Ratio (PAR) are used to address the demand-responsive farm appliance scheduling problem. The performance of the proposed system will be illustrated by several case studies.

In recent times, to achieve food security for all, there is a need to implement the Sustainable Development Goals (SDGs) of the United Nations. If the SDGs are properly implemented, they will provide synergy between energy availability, agricultural production, medical facilities, water treatment, climate change policies, RES, sustainable consumption, infrastructure development, and urban ecosystems [19]. As part of achieving agricultural production for the SDGs, this study aims to propose a FEMS that considers farm appliances and RES. Although the authors in [20] proposed a Metaverses for agriculture under decentralized complex adaptive systems and decentralized autonomous organizations. The proposed systems are employed to achieve sustainable agriculture where ACP theory and federated intelligence are anticipated. Unfortunately, the work in [20] does not considered energy management in smart agriculture. In the proposed system, scheduling of farm appliances is provided while considering different time horizons. This study takes into account a complex energy balance scenario based on energy and load as the number of agricultural appliances increases and unpredictability in electricity consumption is introduced. Farm energy efficiency can primarily be attained either by lowering total farm energy usage or by shifting farm load consumption. Consumption reduction refers to lowering the overall energy load, which is typically accomplished by raising consumer knowledge, turning off farm equipment when it is not in use, buying energy-efficient equipment, or enhancing the structure and design of farms [21]. However, farm energy consumption shifting focuses on delaying certain farm loads over time, typically to off-peak hours, to benefit from remote RES generation and off-peak rates in a liberalized energy market. Noteworthy, these two options can be used in conjunction with one another and are not mutually exclusive [21]. Important decisions about how farm appliances can be controlled must take into account the grid's operational constraints and scheduling strategies to determine the optimal farm load-shifting. Farm appliance scheduling typically takes place across different time horizons that allow for precise forecasting of farm demand and electricity production. In this situation, sufficient and accurate RES profiles of energy production and consumption are needed. Additionally, intelligent farm load-shifting, which maximizes the energy from the self-consumption of RES, is the solution to the basic issue of FEMS. In light of this, the study of FEMS in smart agriculture is crucially important to farm owners and electrical distribution systems.

1.1. Contributions

The contributions of this study are outlined as follows.

i. To propose a conceptualized FEMS based on honey badger optimization algorithm for scheduling of farm appliances.
ii. To minimize energy consumption and PAR while maximizing farmer's comfort by introducing RES.
iii. The proposed FEMS is evaluated using real-time pricing (RTP) and Time-of-Use (ToU) electricity schemes from Enova Power Corp [22].

1.2. Organization of Paper

The remaining part of this paper is organized as follows. Section 2 discusses the related work. Section 3 presents the proposed system model while Section 4 presents the conclusion with future work.

2. THE INTERNET OF AGRICULTURAL THINGS

As an evolving research, IoT in agriculture, known as (IoAT), provides advancements in technology to achieve precision agriculture [23]. Precision agriculture allows for the optimization and improvement of agricultural processes; thereby, providing reliable and fast production. The applicable areas of IoT for agriculture include early disease detection, smart irrigation, crop counting, etc., [23]. The state-of-the art reviews on the IoAT are discussed as follows: The authors in [24] discussed the roles of IoT in smart farming. They also discuss how IoT can be deployed for pest and disease detection, multi-robotic systems, and harvesting based on robots. However, monitoring of pest diseases in real-time is not discussed. Other areas of smart farming, such as irrigation monitoring, crop monitoring, field monitoring, and the method of data collection, are not discussed. The authors in [25] explored the use of unmanned aerial vehicles for smart farming. They consider the detection of fertilizer, irrigation, and diseases. Also, weed detection and field level phenotyping. However, the challenges of the IoT are not considered. Furthermore, data collection was not discussed. The work in [26] discussed smart farming by considering the operational management of intelligent agriculture empowered by IoT. The work also presented a discussion on the technologies for context reasoning and awareness. However, no technological frameworks for smart farming were discussed. Furthermore, the communication and operating systems for IoT technologies were not discussed. The authors in [27] deployed the IoT for irrigation while considering weather conditions. Another work in [28] uses the Analysis of Variance (ANOVA) statistical method to analyze the real-time monitoring of irrigation and river water supply based on the IoT concept. However, none of the authors discuss energy management for smart agriculture.

2.1. Energy Management for Agricultural Sector

Energy management in smart agriculture is a method of alleviating high energy demand from the main grid. Farmers and consumers play critical roles in global food security and economic development. However, developed countries have utilized alternative sources of energy to boost agriculture as compared to under-developed countries. This calls for the management of energy for agriculture to achieve the SDG goals and objectives of food security and ensure food is available for all. In retrospect, conventional sources of energy are mostly used by farmers for animal and crop production. However, it increases the burden on the main grid as the number of energy users increases. Therefore, it is necessary to provide efficient modern management of a farming system that considers the following constraints: energy, economy, and environment. To this end, the authors in [29] formulated a multi-objective genetic algorithm to find the optimal mix of agricultural inputs to minimize greenhouse gas emissions while maximizing the benefit-cost ratio and output energy. However, they did not consider the energy management of agricultural appliances. Also, integrating RES for energy management is not considered. The authors in [30] presented demand-side flexibility of the power system to counterbalance the challenges of the main grid in terms of power fluctuations. They also provided a review that discusses the integration of RES while considering the residential, commercial and industrial energy demand sectors. However, they do not investigate how energy management can be minimized experimentally. The authors in [31] presented a five-year energy exchange based on limiting pumping facilities in different countries. They provided different scenarios with distinct pumping energy reductions while considering the technical parameters of the proposed set-aside scheme. Furthermore, the annual pumping expenditure, payoff of agricultural debt, and rehabilitation of the irrigation network were considered for the assessment of the proposed scheme. However, efficient decision-making is important for energy management in agriculture, which was not considered. Due to uncertainties in energy management, optimal strategies in the planning of energy management systems are paramount. To this end, the authors in [32] proposed a fuzzy-random interval programming model while considering multiple uncertainties. The proposed model combines existing interval linear programming, superiority-inferiority-based fuzzy stochastic programming, and mixed integer linear programming to facilitate capacity-expansion planning of energy-production facilities within a multi-period and multi-option context. Also, the model provides long-term energy management planning for different cities. The objectives achieved were system cost minimization, system reliability, and energy security maximization. The authors in [33] proposed a model based on fuel cell hybrid-driven agricultural tractors. The proposed model optimizes energy flux and increases energy efficiency while minimizing the stress on the fuel cell generators. However, energy management for agricultural appliances is not considered.

3. THE PROPOSED SYSTEM MODEL

The proposed system model is presented in Figure. 1. In the figure, different agricultural appliances are considered for determining energy management in a typical farm environment. Note that all agricultural appliances are connected to each other using a communication line (e.g., smart sockets). As a progressive research, the security of the communication line and entire proposed system will be investigated in future. Each agricultural appliance is connected to a smart meter that monitors its energy consumption rate. The smart meter is an electronic device that measures and monitors energy consumption, voltage levels, and currents of appliances [34]. The agricultural appliances get their source of energy from the main grid; however, when the grid is not available, energy from the RES is used. We consider solar energy in the proposed scenario; however, other RES can be deployed. Energy generated from the RES is stored on a battery system, which will be used at a later time when the energy from the grid is insufficient. It is noticed that the photovoltaic (PV) cells are used for converting sunlight directly to electricity. Here, Maximum Power Point Tracking (MPPT) is deployed to extract the maximum available energy from the PV module under certain conditions [35].

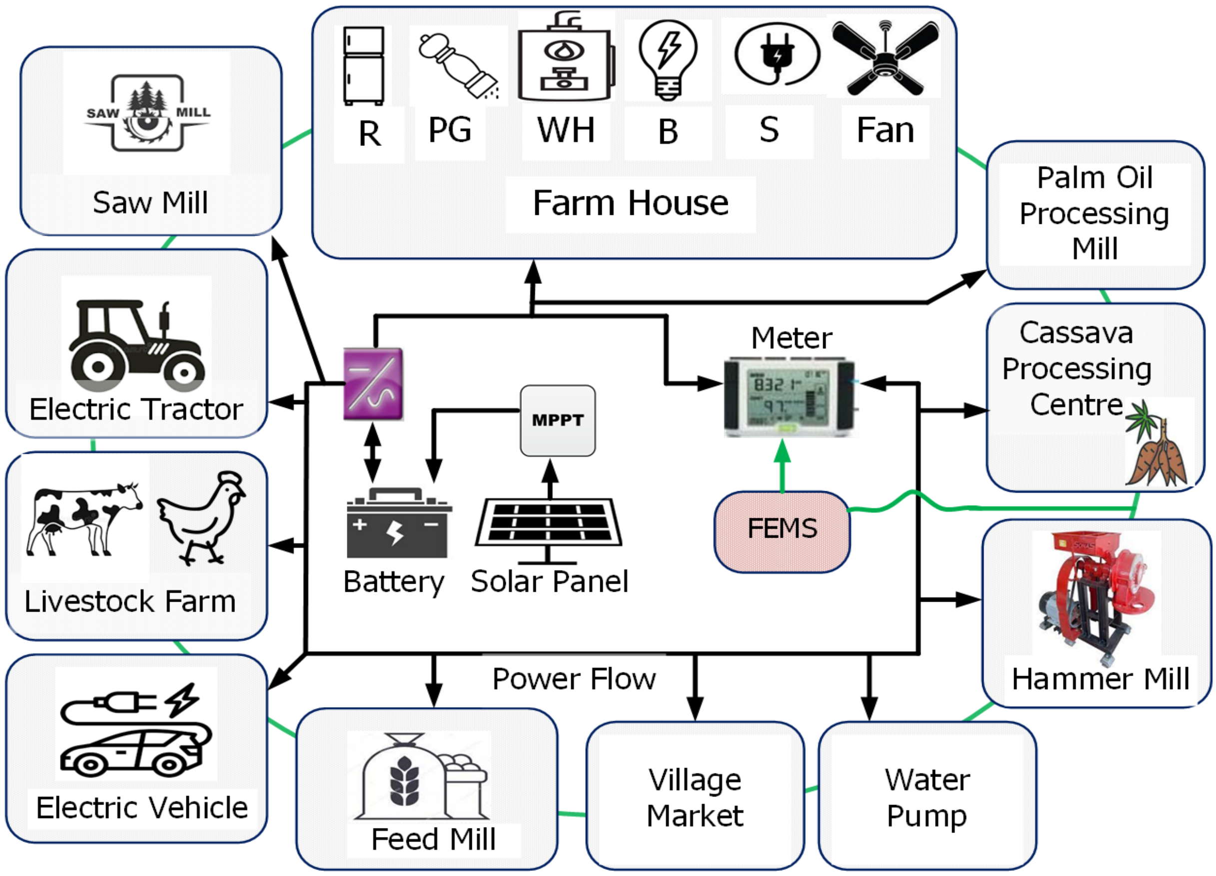

Figure 1: The proposed system model: R: Refrigerator; PG: Pepper grinder; B: electric bulb; WH: Water heater; S: Smart socket; MPPT: Maximum power point tracking; FEMS: Farm energy management system; the black arrow line denotes power flow and green arrow line denotes communication line.

In the proposed system, the FEMS aims to provide load scheduling for the agricultural appliance. Moreover, the focus of this study is to coordinate agricultural appliances for engaging in the FEMS. Considering the farm's electricity usage habit, the agricultural appliances are categorized into two groups. To this end, a multi-objective optimization is formulated for minimizing the peak load and electricity consumption of agricultural appliances. Inspired by the work in [36], the total time horizon is denoted by H. Let's F denotes the set of all agricultural appliances and for each appliance $f \in F$, we assume that f has a predetermined schedulable operational time slots in a day. The set of predetermined schedulable operational time slots of the appliance f is defined as follows:

$$\theta = \{k, k+1, \dots, h-1, h\}, \tag{1}$$

where $k, h \in H, k \leq h$ and the total predetermined schedulable operational time slots is defined as follows:

$$|\theta| = h = k + 1. \tag{2}$$

This study assumes that if agricultural appliances cannot be scheduled, then a fixed amount of operational time is provided. The total energy consumption TC is defined as follows:

$$TC = B_{h,f} E_f, \tag{3}$$

where $h \in H$ and E_f is the fth energy consumption of the farmers.$B_{h,f} = \sum_{h=1}^{H} \sum_{f=1}^{F} b_{h,f}$ is the total number of binary decisions that determine the state of the appliances' operations. It means that the agricultural appliances can be either turned on or turned off. If $b_{h,f} = 0$, then the agricultural appliances are turned off; otherwise, if $b_{h,f} = 1$, then the agricultural appliances can be turned on. Note that F is the total number of agricultural appliances. In Section 3.1, this study discusses the grouping of agricultural appliances.

3.1. Agricultural Appliances Grouping

In this study, agricultural appliances are grouped into fixed and non-fixed appliances. The grouping is based on the operational capabilities of the agricultural appliances. Besides, some agricultural appliances can either be scheduled or unscheduled. Fixed agricultural appliances are those that operate at predetermined time slots, especially during the day and night. Also, fixed agricultural appliances such as refrigerators are not schedulable. The non-fixed agricultural appliances are those that can be scheduled easily. Besides, non-fixed agricultural appliances can be interrupted, which means that they can be halted while in operation. On the other hand, non-fixed agricultural appliances may be uninterruptible, which implies that once they start up, they cannot be stopped from operating.

3.2. Agricultural Scheduling without RES

We consider the power loads for all agricultural appliances as non-fixed appliances. To calculate the total power loads, we consider the power ratings of all agricultural appliances, which are defined as follows:

$$TL = \sum_{h=1}^{H} \sum_{f=1}^{F} L_f \, B_{h,f}, \tag{4}$$

where L_f is the power ratings fth agricultural appliances. The subscripts f, and h denote appliances of farmers and operational timeslots of appliances. H denotes the total operational timeslots, F represents total number of appliances of farmers, the subscript $peak$ denotes peak timeslot, and avg indicates average. The peak load is calculated as:

$$L_{peak} = \max_{f\in F} [\sum_{h=1}^{H} \sum_{f=1}^{F} L_f \, B_{h,f}], \tag{5}$$

whereas, the average hourly power load is defined as:

$$L_{avg} = \frac{1}{H} \sum_{h=1}^{H} \sum_{f=1}^{F} L_f \, B_{h,f}, \tag{6}$$

For fixed agricultural appliances, the total load, which was calculated in Equation 4 is rewritten as follows.

$$TL = \sum_{h=1}^{H} \sum_{f=1}^{F} L_f \, \theta_h. \tag{7}$$

The hourly average power load of Equation 6 is rewritten for fixed agricultural appliances as:

$$L_{avg} = \frac{1}{H} \sum_{h=1}^{H} \sum_{f=1}^{F} L_f \, \theta_h, \tag{8}$$

3.2.1. Peak to average ratio

The PAR of electricity is computed as the ratio of the given peak power to the given average power, which is calculated as follows [36]:

$$PAR = \min_{f\in F} \left[\frac{L_{peak}}{L_{avg}}\right],$$

$$= \min_{f\in F} [\frac{\max_{f\in F} \sum_{h=1}^{H} \sum_{f=1}^{F} L_f \theta_h}{\frac{1}{H} \sum_{h=1}^{H} \sum_{f=1}^{F} L_f \theta_h}],$$

Such that

$$B_{h,f} = \sum_{h=1}^{H} \sum_{f=1}^{F} b_{h,f} = \theta_h,$$

$$h \in H; f \in F;\ B_{h,f} \in [0,1]. \tag{9}$$

3.2.2. Electricity consumption minimization

In a smart agricultural environment, the farmers focus more on electricity consumption minimization; whereas the main grid is concerned with peak load minimization. The farmers' electricity consumption minimization is defined as follows [36]:

$$\min_{f\in F} \sum_{h=1}^{H} (P_h (\sum_{f=1}^{FI} \left(L_f B_{h,f}\right) + \sum_{f=1}^{NFI} (L_f B_{h,f}))),$$

Such that

$$\sum_{f=1}^{FI} \left(L_f B_{h,f}\right) + \sum_{f=1}^{NFI} (L_f B_{h,f}) \leq Q,$$

$$\sum_{h=1}^{H} \sum_{f}^{FI} B_{h,f} = \theta_h;\ \sum_{h=1}^{H} \sum_{f=1}^{NFI} B_{h,f} = \theta_h, \tag{10}$$

where Q is the system load capacity, $FI \in F$ denotes the number of fixed appliances and NFI denotes the number of non-fixed appliances. P_h is the hourly electricity price, which can either be real-time pricing or ToU pricing schemes. We consider a 24-hour pricing horizon for which the utility company charges the farmers at time slot h. As progressive research, we will the future consider the Critical Peak Pricing (CPP) scheme [37] and the Day-ahead Pricing (DAP) scheme [38].

3.3. Agricultural Scheduling with RES

In the absence of energy from the main grid, RES serves as an alternative energy source for farmers. The energy harvested from the solar panels is stored in a battery system. The rated charging and discharging of the battery at a certain time slot h are denoted by L_h^{charg} and $L_h^{discharg}$, respectively. The superscripts $charg$ and $discharg$ represent charging and discharging, respectively. Let $D_{h,f}$ denotes the binary decision for charging and discharging the battery. If $D_{h,f} = 1$, it implies that the battery is charging; otherwise, if $D_{h,f} = 0$, it means that the battery is discharging. Note that the rates of charging and discharging are mutually exclusive. The charging and discharging energy of the battery is defined as follows:

$$CDE_h = \begin{cases} L_h^{charg} D_{h,f}, & if\ (D_{h,f} == 1), \\ L_h^{discharg} D_{h,f}, & Otherwise \end{cases}. \tag{11}$$

We denote L_{max}^{charg} and $L_{max}^{discharg}$ to the maximum charging and discharging of the battery, respectively. Also, μ^{charg} and $\mu^{discharg}$ denote the charging and discharging efficiencies, respectively. In this study, we assume that the battery cannot charge and discharge at the same time; hence, it is formulated as follows:

$$\frac{L_h^{charg}}{\mu^{charg} L_{max}^{charg}} + \frac{L_h^{discharg}}{\mu^{discharg} L_{max}^{discharg}} \leq 1, \tag{12}$$

where $\frac{L_h^{charg}}{\mu^{charg} L_{max}^{charg}}$ is the state of charging and $\frac{L_h^{discharg}}{\mu^{discharg} L_{max}^{discharg}}$ is the state of discharging. The state of charge (SOC) is also considered in this study, where the minimum and maximum SOC are denoted by σ_{min}^{soc} and σ_{max}^{soc}, respectively. The minimum and maximum battery energy levels are defined in Equation 13 and Equation 14, respectively.

$$E_h^{min} = \sigma_{min}^{soc} \mu^{charg} L_h^{charg} B^{cap}, \tag{13}$$

$$E_h^{max} = \sigma_{max}^{soc} \mu^{discharg} L_h^{discharg} B^{cap}, \tag{14}$$

where B^{cap} is the battery capacity. The superscript cap denotes capacity. The energy balance for the battery is defined as follows:

$$E_h^{min} \leq E_h^b \leq E_h^{max}, \tag{15}$$

where E_h^b is the battery energy level and is defined as follows:

$$E_h^b = E_{h-1}^b + \mu^{charg} L_h^{charg} D_{h,f} + \frac{L_h^{discharg}}{\mu^{discharg}}, \tag{16}$$

The initial battery energy level is given as E_0^b. Hence, the energy balance is defined as $E_0^b \leq E_h^b \leq E_h^{max}$. The superscript b denote battery. Note that the battery energy level should be non-negative and the total battery energy level should not be more than the battery capacity.

3.4. The Honey Badger Optimization Algorithm

Inspired by the work in [39], the Honey Badger Optimization Algorithm (HBOA) is adopted in this study for achieving the multi-objective functions for smart agriculture. The HBOA behaves like the honey badger. In the rain forest and semi-desert of Africa and Asia subcontinent, the honey badger mammal is often found. There are certain skills that the honey badger used to locate its prey such as continuous slow walking and smelling mouse. The exact location of prey is determined via digging and afterwards, the prey is ultimately caught. From its name, honey badger loves honey; however, it does not easily identify beehives. Contrarily, a bird known as honey-guide, assists the honey badger to local the beehives. Both animals have mutual benefits as the honey badger uses it long claws to open hives for the bird, while the bird helps honey badger to locate the beehives [39]. The mathematical formulation of the HBOA is presented in the following algorithmic steps:

3.4.1. Step 1: Population initialization

In this study, an initial random population is generated for the HBOA. The number of honey badgers determine the total number of random populations N; hence, the initial population is defined in Equation 17.

$$x_i = lb_i + (up_i - lb_i)r, \tag{17}$$

where $i \in N$ and lb_i and up_i are the population lower and upper bound, respectively. r is a random number between 0 and 1. The number of honey badgers is used to define the number of decision variables and number of agricultural appliances. The generated population becomes the position for either the honey badger or prey.

3.4.2. Step 2: Smell intensity

The strength of prey and the distance between the prey and the ith honey badger are considered to determine the smell intensity of the prey. Considering the inverse square law [40], and applying the law of conservation of energy, the smell intensity (known as intensity of position) is defined as follows:

$$I = \frac{S}{4\pi z^2}\beta,$$
$$S = (x_{i+1} - x_i)^2,$$
$$z = (x_{prey} - x_i), \tag{18}$$

where $\beta \in [0,1]$ is the adjustment parameter that regulates the smell intensity. If $\beta \geq 0.5$, then the honey badger has a high smell intensity and vice versa. S is the source of strength or position of the prey and z is the distance between prey and thhoney badger. Also, the final position is denoted by x_{i+1} and the initial position is denoted by x_i.

3.4.3. Step 3: Time factor update

While taking into account time variable randomness, a time factor represented by α is used to secure the shift from exploration to exploitation. The following is the definition of a time factor update:

$$\alpha = \exp(\frac{-\varrho}{\varrho_{max}}), \tag{19}$$

where ϱ_{max} is the maximum number of iterations. To avoid falling into local optimum, a flag denoted by ϕ is used to alter the search direction, which allows the honey badgers to rigorously scan the search space. The flag ϕ is formulated as follows:

$$\phi = \begin{cases} 1, if\,(r \leq 0.5), \\ -1, \;\; otherwise' \end{cases} \tag{20}$$

where $r \in [0,1]$.

3.4.4. Step 4: Honey badger position update

The adopted the new position x_{new} of HBOA process is split into two distinct phases, i.e., digging and honey phases. The subscript new denotes index of new population.

i. **Digging phase:** The honey badger acts in a manner like the cardioid motion [40]. For instance, consider rotating a circle with a specified radius around another circle with a similar radius. Set a point on the moving circle, then as it circles the circumference of the still one, trace the route of that point. That point follows a cardioid path. The digging phase is formulated as:

$$x_{new} = x_{prey} + \phi\varphi I x_{prey} + \phi r\alpha z(1 + \cos(2\pi r)), \tag{21}$$

where $\varphi \geq 1$ is the honey badger's capacity to obtain food, x_{prey} is the position of the prey and $r \in [0,1]$. The subscript $prey$ denotes the index of prey population. In this phase, the honey badger significantly relies on the smell intensity of the prey I, the prey x_{prey}, the distance between the prey and the ith honey badger (z), and the time-varying factor (α). Also, during the digging phase, honey badgers may experience any ϕ disturbances that help them locate better prey positions.

ii. **Honey Phase:** The scenario in which a honey badger follows a honey guide—a bird—to the beehives is as follows:

$$x_{new} = x_{prey} + \phi r\alpha z, \tag{22}$$

where $r \in [0,1]$. The honey badger searches the area near the positions of its prey x_{prey} while considering z, and ϕ. Search behavior that varies over time α, has an impact on the search space. A honey badger may also detect the disturbance ϕ.

Algorithm 1 describes the proposed HBOA for FEMS. In the algorithm, the anticipated electricity prices such as RTP and ToU pricing schemes are considered. However, this study is not limited to the pricing schemes but other pricing schemes like day-ahead pricing, dynamic pricing, critical peak pricing (CPP) can be considered in future study. All algorithm parameters and model variables are initialized at the start of the algorithm. Besides, the decision variables are assigned on the basis of the number of farm appliances. A randomized initial population is obtained, which is optimized using the honey badger algorithm. The electricity price and energy consumption are minimized alongside the PAR while the farmers' comfort is maximized.

Algorithm 1: The proposed farm energy management system using honey badger optimization algorithm

1: **Input Initialization:** RTP and ToU pricing schemes, agricultural operational start and end time, fixed time slots, non-fixed time slots, farmers energy usage pattern, and RES, system load capacity Q, maximum and minimum energy level, minimum and maximum SOC, battery capacity, charging and discharging battery efficiencies

Parameter Initialization: Maximum iteration ϱ_{max}, population size, total time horizon, total number of fixed appliances, total number of non-fixed appliances, smell intensity (I), flag (ϕ), distance between the prey and ith honey badger z.

For $h = 1$ to H **do**
Evaluate the fitness of each honey badger position f_i using the objective function and assign to f_i where $i \in F$
Save the best position x_{prey} and assign fitness to f_{prey}
$\varrho = 1$
while ($\varrho \leq \varrho_{max}$) **do**
Update the time factor α using Equation 19
Compute the smell intensity using Equation 18
if ($r \leq 0.5$) **then**
Update the new position x_{new} using Equation 21
else
Update the new position x_{new} using Equation 22
end if
Evaluate the new position and assign f_{new}
if ($f_{new} \leq f_i$) **then**
Set $x_i = x_{new}$ and $f_i = f_{new}$
end if
if ($f_{new} \leq f_{prey}$) **then**
Set $x_{prey} = x_{new}$ and $f_{prey} = f_{new}$
end if
for $f = 1$ to F **do**
Set fixed time slots
Compute the unscheduled energy consumption and total load using Equation 3 and Equation 4, respectively
Set time slots using Equation 1
Generate binary decision
Compute the total energy consumption using Equation 3
Compute the total load using Equation 7
Solve the PAR using Equation 9
Compute the energy consumption minimization objective function using Equation 10
Evaluate energy consumption based on RES and battery storage system
end for
$\varrho = \varrho + 1$
end while
end for

4. SIMULATION RESULTS

In this section, the experimental description and parameters used to implement the proposed model are presented. Table 1, Table 2, and Table 3 show the agricultural appliances, electricity schemes and values of parameters used in the paper.

Table 1: Agricultural appliances used in this study

Appliances/Building	Power Rating (kW)	LoT (h)
Hammer mill	2	7
Pepper grinder	2	1
Refrigerator	6	18
Saw mill	5	10
Palm oil processing mill	50	8

Appliances/Building	Power Rating (kW)	LoT (h)
Electric ceiling fans	0.2	16
Cassava processing centre	15	8
Electric vehicle	12	5
Tractor	12	7
Smart Socket	3.6	22
Water Pump	1	8
Village market	100	14
Bulb	0.6	12
Feed mil	20	8
Livestock farm	20	16
Water heater	2	3

Table 2: Electricity pricing schemes used in this study [22]

Hour	ToU Scheme	RTP Scheme
1	15.1	9.83
2	15.1	8.63
3	15.1	8.87
4	15.1	12
5	15.1	9.19
6	10.2	12.27
7	10.2	20.69
8	10.2	26.82
9	10.2	27.35
10	10.2	17.31
11	10.2	16.42
12	15.1	16.44
13	15.1	16.19
14	7.4	13.81
15	7.4	8.87
16	7.4	8.35
17	7.4	8.65
18	7.4	9.35
19	7.4	8.11
20	7.4	8.25
21	7.4	8.10
22	7.4	8.14
23	7.4	8.13
24	7.4	8.34

Table 3: Parameters used in this study [39]

Parameter	Description	Value
H	Operational time	24-h
F	Number of farm appliances	16
ϱ	Number of iterations	1000
lb	Lowe population bound	-10
up	Upper population bound	10
N	Number of populations	30
ϕ	Vector flag for foraging	[-1,1]
β	Adjustment parameter that regulates the smell intensity	0.7
φ	Honey badger's capacity to obtain food	6

4.1. Evaluation of the Proposed System Model Convergence

In this paper, we compared the honey badger algorithm with different electricity pricing schemes to determine its superiority in terms of energy cost load minimization. Besides, Figure 2 shows the convergence analysis of the honey badger algorithm employed for smart agriculture. It is observed from the results that convergent is reached at the 400th iterations. The global best value means that convergence of the algorithm can be achieved within a reasonable number of iterations. Hence, premature convergence is avoided. Furthermore, the global best value allows us to get the more reliable solutions for optimization.

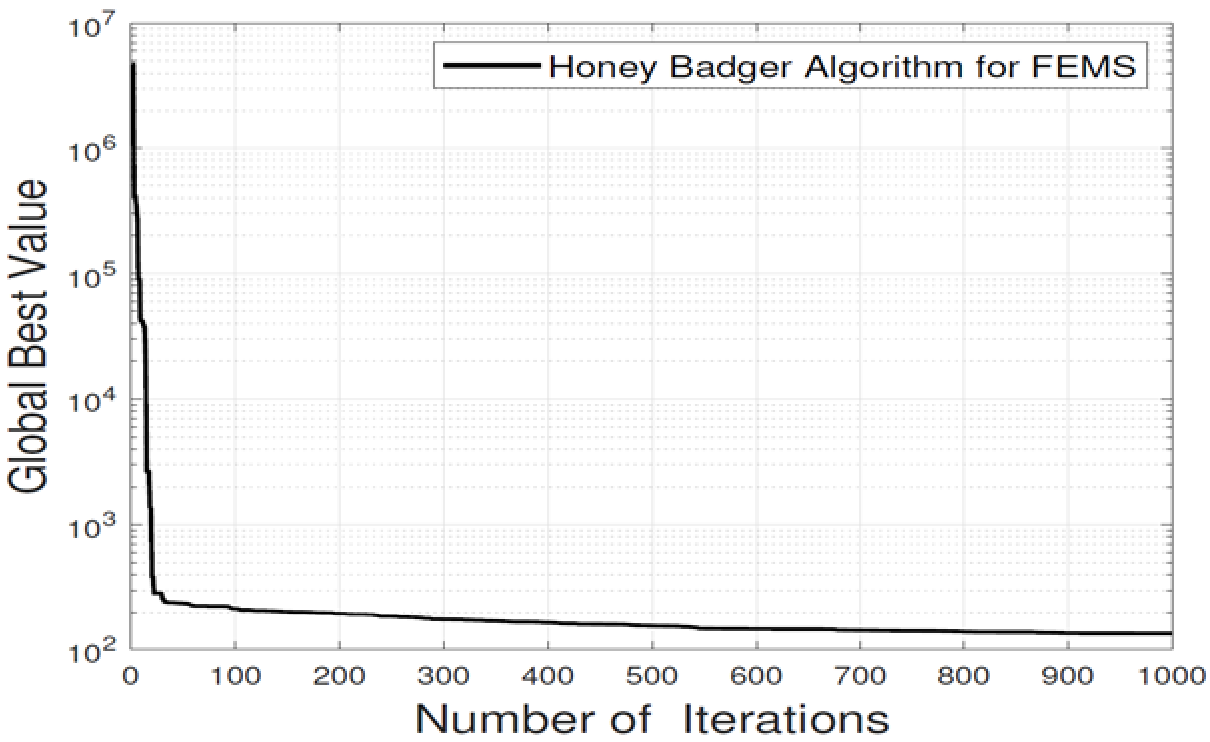

Figure 2: Convergence analysis of the proposed model

4.2. Evaluation of the Proposed System in Terms of Time of Use Pricing Scheme

In this section, two pricing schemes such as time of use (ToU) and real time pricing (RTP) are considered for analyzing the efficacy of the proposed FEMS. It is observed from the results in Figure 3 that the electricity cost with FEMS continuously increases during the off-peak and on-peak hours. The maximum electricity cost is 3500 kwh. It is observed from the figure that when using FEMS without RES, electricity cost becomes unstable; however, it shows high electricity cost during the timeslots of 1-5 hours and decreases in subsequent hours. The change in electricity cost depicts the dynamic behavior of farmers electricity consumption and farm appliances usages. When FEMS with RES is deployed, a reduced electricity cost is observed for the different timeslots. Besides, the proposed FEMS helps to schedule farm appliances from on-peak to off-peak hours or to the period when electricity prices are minimal. In Figure 3, without FEMS, there are high electricity costs during the off-peak hours, which occur as a result of a lack of scheduling mechanisms. Most appliances with high loads are manually scheduled to operate during the off-peak hours, thereby leading to high electricity costs during the off-peak time.

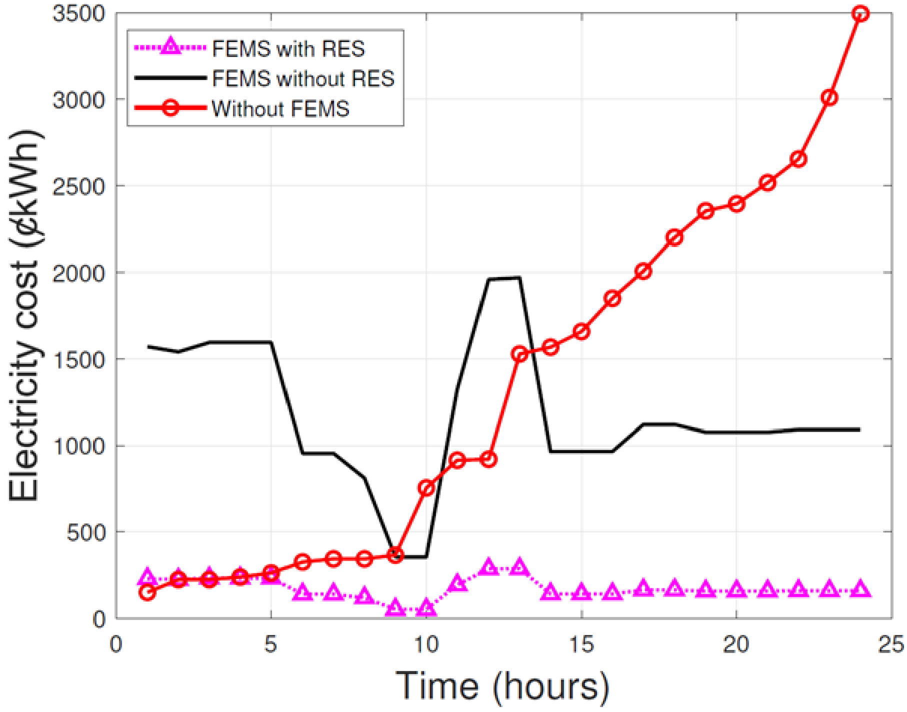

Figure 3: Electricity cost (ToU)

slots. The rationale behind Figure 3 is that different scenarios are considered to evaluate the performance of the proposed FEMS at different timeslots. This shows the dynamic behaviors of the farmers when FEMS is used without RES, with RES, and without FEMS. Also, it is observed that the load consumption is high during the 1-15 hours as shown in Figure 4. In the figure, FEMS with RES shows a minimal load consumption as compared to FEMS without RES and without FEMS, respectively. Table 4 shows that the total cost for without FEMS is 33230, 28214 for FEMS without RES and 4107.60 for FEMS with RES. Whereas, the max load for FEMS with RES is 18.85kW against 151.40 kw for FEMS without RES and 246.80 kw for without FEMS. The results explain the advantages of deploying FEMS in terms of electricity cost and load consumption minimization.

In Figure 4, without FEMS, there are unstable load consumptions at different timeslots. It implies that when the load is unscheduled, appliances that have high power ratings are made to operate with 1–19 time slots, thereby increasing the load consumption of the proposed systems along with the increase in electricity costs. Therefore, the farmers pay more during the on-peak and off-peak hours when the TOU pricing scheme is considered. As compared to FEMS without RES and FEMS with RES, FEMS without RES shows stable electricity load consumption during 10–16 timeslots, which means that during the on-peak hours, the loads remain stable and reduce during the 9–10 time slots of the off-peak hours. Moreover, FEMS with RES shows reduced load consumption for all timeslots as compared to FEMS without RES and without FEMS, respectively. It implies that RES is efficient at supplying electricity when energy from the grid is insufficient for the ToU pricing scheme scenario. In Figure 3 and Figure 4, the performance evaluation of the proposed system without FEMS, FEMS with RES, and FEMS without RES is discussed. This explains the importance of deploying the proposed FEMS to efficiently manage energy costs and consumption in a commercial smart agriculture scenario; thus, ToU and RTP pricing schemes are used for the evaluations.

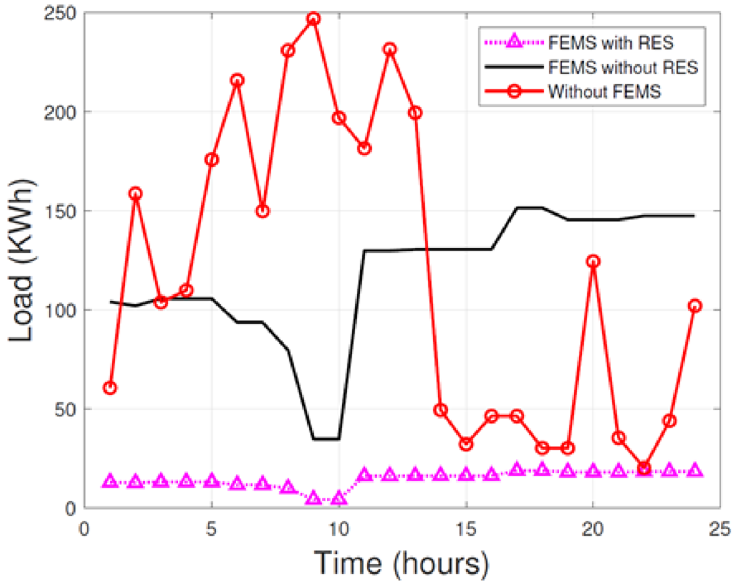

Figure 4: Load consumption (ToU)

Table 4: Analysis of proposed system in terms of total cost and load for time of use pricing scheme

	Total Cost	Max Load	Min Load	PAR
Without FEMS	33230	246.80	20.20	4.41
FEMS without RES	28214	151.40	34.80	1.66
FEMS with RES	4107.60	18.852	4.33	1.66

4.3. Evaluation of the Proposed System in Terms of Real-time Pricing Scheme

In Figure 5, RTP scheme is considered to analyze the efficiency of the employed honey badger optimization algorithm. It is shown from the figure that the electricity cost with FEMS continuously increase from 1-24 hours as compared to electricity costs with FEMS and FEMS with RES, respectively. Moreover, when considering FEMS without RES and FEMS with RES, the electricity cost lies within 27732 and 31197 (see Table 5) as compared to without FEMS.

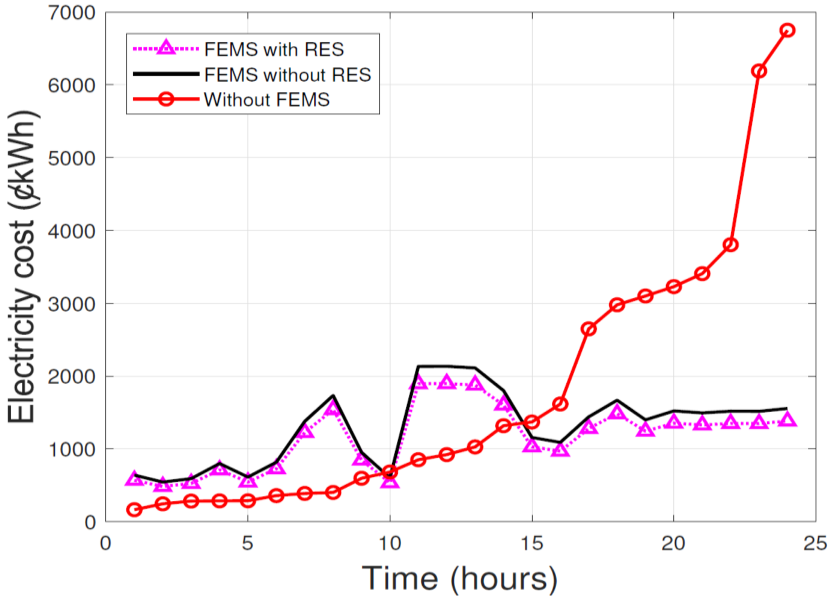

Figure 5: Electricity cost (RTP)

Table 5: Analysis of proposed system in terms of total cost and load for real time pricing scheme

	Total Cost	Max Load	Min Load	PAR
Without FEMS	42893	246.80	20.20	4.41
FEMS without RES	31197	186.40	34.80	2.51
FEMS with RES	27732	90.68	16.93	2.51

In Figure 6, the load consumption for with FEMS is high during the 1-13 hours as compared to FEMS without RES and FEMS with RES, respectively. However, it is observed from the figure that during the 16-24 hours, FEMS without RES has the highest load consumption.

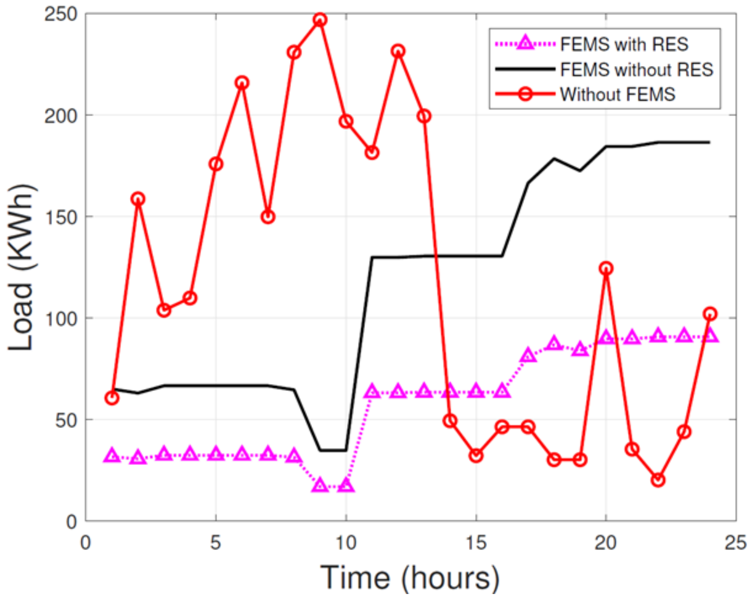

Figure 6: Load consumption (RTP)

5. CONCLUSION AND FUTURE WORK

In this study, optimization is essential for addressing energy management problems in smart agriculture. This work used the honey-badger optimization algorithm to propose an effective energy management system for smart agriculture. The proposed system takes commercialized agriculture into account and incorporates renewable energy sources to ameliorate the burden on the main grid. To ascertain the effectiveness of the proposed system, extensive experiments were conducted, which showed that scheduling farm appliances in response to real-time pricing and time-of-use pricing schemes in the electrical market can reduce load consumption and electricity costs as compared to a system without a farm energy management system. The simulation results showed that a system without FEMS has a high electricity cost of 50.69% as compared to 43.04% for FEMS without RES and 6.27% for FEMS with RES when considering the ToU market price. For RTP market price, a system without FEMS has an electricity cost of 42.3%, as compared to 30.64% for FEMS without RES and 27.24% for FEMS with RES. Besides, the maximum load consumption for a system without FEMS is 246.80 kW, as compared to 151.40 kW for FEMS without RES and 18.85 kW for FEMS with RES when considering the ToU market price. Also, for RTP market price, the maximum load consumption for a system without FEMS is 246.80 kW, as compared to 186.40 kW for FEMS without RES and 90.68 kW for FEMS with RES.

In the future, this study aims to compare the proposed system with existing optimization algorithms in the literature. Also, factors that may affect load consumption and electricity costs in smart agriculture will be investigated and incorporated into problem formulation. Furthermore, a game-theoretical approach will be considered for efficient energy management in smart agriculture.

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