ISSN: 2583-5637 (Online)
International journal of Inventive Research in Science and Technology
Volume 5 Issue 1 January 2026

A Review of Artificial Bee Colony Algorithms for V2X Systems

Sumit Niware[1], Saurabh Gupta[2], Devendra Sharma[3],

Sumitniware20@gmail.com[1], Saurabhgupta.sgsits@gmail.com[2],

devendrasharma798@gmail.com[3],

[1]MTech Scholar, Department of Electrical and Electronics Engineering, Technocrats Institute of Technology, Bhopal, India

[2] Professor, Department of Electrical & Electronics Engineering, Technocrats Institute of Technology, Bhopal, India

[3] Assistant Professor, Department of Electrical & Electronics Engineering, Technocrats Institute of Technology, Bhopal, India

Abstract:

The paradigm shift from vehicles as mere energy consumers to proactive, mobile energy storage units (ESUs) in Vehicle-to-Everything (V2X) ecosystems presents a formidable optimization challenge. The core complexity lies in orchestrating bidirectional energy flows amidst stochastic variables—renewable generation, driving patterns, grid demands, and electricity prices. Conventional analytical optimization methods often falter in this high-dimensional, non-linear, and dynamic environment. Consequently, bio-inspired metaheuristic algorithms, particularly the Artificial Bee Colony (ABC) algorithm, have emerged as powerful tools for near-optimal, real-time decision-making. This paper presents a comprehensive systematic review of research dedicated to optimizing bidirectional V2X energy flows using ABC and its hybridized variants.

We first delineate the V2X optimization landscape, formalizing its core objectives, constraints, and stochastic elements. A primer on the ABC algorithm explains its suitability for this domain. The review then meticulously categorizes and analyzes extant literature across three primary V2X applications: Grid-to-Vehicle/Vehicle-to-Grid (G2V/V2G) for grid services, Vehicle-to-

Home/Building (V2H/V2B) for local energy management, and integrated multi-modal ecosystems. The analysis reveals ABC's proficiency in cost minimization, peak shaving, renewable integration, and grid stability enhancement, often outperforming benchmarks like Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) in convergence speed and solution quality. Furthermore, we explore advanced hybrid ABC models that fuse its exploratory strength with the exploitation prowess of other techniques to overcome local optima stagnation. The paper concludes by identifying persistent challenges—including ultra-large-scale scalability, real-world validation gaps, and cybersecurity considerations—and proposes future research trajectories toward robust, decentralized, and truly intelligent V2X energy networks.

Keywords: Vehicle-to-Everything (V2X), Artificial Bee Colony Algorithm, Bidirectional Energy Flow, Smart Grid, Renewable Energy Integration, Metaheuristic Optimization, Energy Management System, Electric Vehicles.

1. Introduction

The global electrification of transportation, propelled by climate imperatives and technological advancements, is rapidly transforming the automotive landscape. However, the vision of a sustainable future extends beyond mere replacement of internal combustion engines. The concept of Vehicle-to-Everything (V2X) positions Electric Vehicles (EVs) as dynamic assets within a broader energy nexus [1]. V2X encompasses several modes: **Vehicle-to-Grid (V2G)**, where EVs supply power to the electrical grid; **Vehicle-to-Home/Building (V2H/V2B)**, where they power local premises; **Vehicle-to-Vehicle (V2V)** for peer-to-peer energy exchange; and **Vehicle-to-Load (V2L)** for powering arbitrary loads [2]. This bidirectional capability unlocks unprecedented flexibility, enabling EVs to act as distributed energy resources (DERs), providing grid ancillary services, enhancing renewable energy utilization, and offering economic benefits to owners.

Yet, this potential is tempered by significant technical and computational challenges. The core problem is the **Optimization of Bidirectional Energy Flows (OBEF)**. This involves determining the optimal schedule for charging (G2V) and discharging (V2X) for a fleet of EVs, considering multiple, often conflicting objectives:

- **Economic:** Minimizing electricity costs for consumers/aggregators, maximizing revenue from grid services.
- **Technical:** Maintaining grid stability (frequency regulation, voltage support), reducing peak demand, minimizing grid losses.
- **User-Centric:** Guaranteeing driver mobility needs (sufficient battery state-of-charge, SOC), minimizing battery degradation.
- **Environmental:** Maximizing the consumption of locally generated renewable energy (e.g., from solar PV).

This optimization is constrained by EV battery dynamics (capacity, charge/discharge rates, efficiency), grid interconnection limits, user trip schedules, and market rules. Crucially, it must contend with profound **uncertainty** in renewable generation, electricity prices, and EV arrival/departure times and energy demands.

Traditional optimization techniques, such as linear programming (LP) or mixed-integer linear programming (MILP), struggle with the non-linear, non-convex, and combinatorial nature of this problem, especially at scale. This has catalyzed the adoption of **metaheuristic algorithms**—population-based, stochastic search methods inspired by natural phenomena. Among these, the **Artificial Bee Colony (ABC)** algorithm, modeled on the foraging behavior of honey bees, has demonstrated remarkable efficacy and has become a subject of intensive research in V2X optimization [3].

This paper provides a systematic review of the application of ABC algorithms for OBEF in hybrid V2X ecosystems. It synthesizes findings from a broad corpus of research, analyzes the algorithm's adaptations and hybridizations, compares its performance, and outlines a roadmap for future inquiry.

2. The V2X Optimization Problem: Formulation and Challenges

A generic formulation of the OBEF problem is essential to contextualize the role of optimization algorithms.

2.1 Core Objective Functions

Research typically focuses on single or multi-objective formulations:

1. **Cost Minimization:** Min Σ_t [(Cost of Grid Purchase_t) - (Revenue from V2X_t) + (Battery Degradation Cost_t)].
2. **Peak Demand Shaving:** Min (Max(Net Load_t)), where Net Load = Base Load + EV Charging - EV Discharging - Renewable Generation.
3. **Renewable Self-Consumption Maximization:** Max Σ_t min(Renewable Generation_t, Local Load_t + EV Charging_t).
4. **Grid Loss Minimization:** Min Σ_t (I^2R losses) across distribution feeders.
5. **Frequency Regulation/Voltage Support:** Track a grid signal by modulating aggregate EV power.

2.2 Key Constraints

- **EV Battery Dynamics:** SOC_(t+1) = SOC_t + (η_c * P_c_t * Δt) - (P_d_t / η_d * Δt).
- **SOC Boundaries:** SOC_min ≤ SOC_t ≤ SOC_max.
- **Power Limits:** 0 ≤ P_c_t ≤ P_c_max; 0 ≤ P_d_t ≤ P_d_max.
- **Driving Needs:** SOC_departure ≥ SOC_required_trip.
- **Grid Power Limits:** P_grid_min ≤ Σ(P_ev_t) ≤ P_grid_max.
- **V2X Availability:** P_d_t > 0 only when the EV is plugged in and available.

2.3 Sources of Uncertainty and Complexity

The "hybrid" nature of V2X ecosystems refers to the confluence of diverse, stochastic elements:

- **Renewable Generation (PV/Wind):** Intermittent and weather-dependent.
- **EV Mobility Patterns:** Stochastic arrival/departure times, initial SOC, and trip energy consumption.

- **Electricity Markets:** Fluctuating real-time or time-of-use prices.
- **User Behavior:** Willingness to participate, preference settings.

This high-dimensional, constrained, stochastic optimization problem is a quintessential candidate for robust metaheuristic solvers like ABC.

3. The Artificial Bee Colony Algorithm: A Primer and Rationale for V2X

Proposed by Derviş Karaboğa in 2005, the ABC algorithm simulates the intelligent foraging behavior of a honeybee swarm [4]. The colony consists of three groups:

1. **Employed Bees:** Associated with specific food sources (solution candidates). They explore their vicinity and share information with onlookers.
2. **Onlooker Bees:** Evaluate the nectar amount (fitness) of food sources discovered by employed bees and probabilistically choose richer sources to exploit further.
3. **Scout Bees:** Abandon exhausted food sources (solutions that do not improve over a limit) and discover new ones randomly, ensuring exploration.

Why ABC for V2X Optimization?

- **Balance of Exploration and Exploitation:** The distinct roles of employed, onlooker, and scout bees create a natural balance between global search (exploration) and local refinement (exploitation), crucial for navigating the complex V2X solution space without premature convergence.
- **Few Control Parameters:** Primarily requires tuning colony size and the "limit" for scout generation, making it relatively simple to implement compared to algorithms like PSO or GA, which require tuning inertia weights, crossover, and mutation rates.
- **Robustness:** Demonstrates strong performance on multimodal and non-linear problems, which are characteristic of V2X models with numerous local optima.
- **Population-Based Parallelism:** Inherently suitable for parallel computation, a valuable trait for scaling to large EV fleets in real-time energy management systems (EMS).

4. Review of ABC Applications in V2X Domains

4.1 Grid-Focused Optimization (V2G/G2V)

The majority of research applies ABC to **aggregator-level** problems, where an entity coordinates a fleet of EVs to provide grid services.

- **Frequency Regulation and Peak Shaving:** Researchers have frequently used ABC to schedule EV fleets for primary frequency response. The algorithm's ability to quickly find feasible schedules that track a frequency deviation signal has been noted as superior to GA in terms of convergence speed and final solution cost [5]. For peak shaving, ABC is used to determine the optimal discharging power of EVs during peak hours while ensuring charging during off-peak periods, flattening the daily load profile. Comparative studies often show ABC achieving lower peak-to-average ratios than rule-based methods and comparable or better results than PSO with faster computation times for medium-sized fleets (100-1000 EVs) [6].
- **Economic Dispatch with V2G:** In microgrid or distribution network scenarios, ABC is employed to solve economic dispatch problems that include V2G as a controllable resource. The objective is to minimize total generation cost from conventional units while integrating renewables and V2G. ABC has been effective in handling the integer variables (EV status) and non-linear cost functions, often finding lower-cost solutions than traditional methods like quadratic programming when non-convexities are introduced [7].
- **Uncertainty Handling:** Advanced studies integrate ABC with stochastic or robust optimization frameworks to manage uncertainty. For instance, a two-stage model might use scenario generation for renewable output and EV availability, with ABC solving the second-stage scheduling problem for each scenario. Hybridization with fuzzy logic or chance-constrained programming within the ABC fitness evaluation is also explored to soften constraints related to driver satisfaction under uncertainty [8].

4.2 Local Energy Management (V2H/V2B)

At the residential or commercial building level, ABC optimizes energy flows between EVs, local renewables (PV), the building load, and the grid.

- **Home Energy Management Systems (HEMS):** ABC is embedded in HEMS to minimize the household electricity bill. The algorithm schedules the operation of the EV, battery storage, and deferrable appliances. Research demonstrates that ABC-based HEMS can achieve cost savings of 15-30% compared to uncoordinated charging, while also increasing PV self-consumption by 20-40% [9]. Its efficiency in solving this mixed-integer problem with time-dependent constraints (e.g., EV availability only during evenings) is a key advantage.
- **Office Buildings/Commercial V2B:** For workplace charging, ABC optimizes the use of EV fleets (employees' cars) to shave the building's peak demand, which incurs high demand charges. The algorithm must solve a larger-scale problem with more homogeneous arrival/departure patterns. Studies show that ABC effectively reduces the monthly demand charge while ensuring all vehicles are sufficiently charged for the homeward journey, outperforming first-come-first-serve (FCFS) and simple threshold-based strategies [10].

4.3 Integrated Multi-Modal V2X Ecosystems

The most complex application involves hybrid ecosystems where an EV can interact with multiple entities.

- **V2H + V2G:** Here, the EV must serve both home energy needs and respond to grid signals. ABC is used to prioritize and arbitrate between these services based on real-time prices or grid emergency signals. Multi-objective ABC (MOABC) variants, often based on Pareto dominance, are applied to find trade-off solutions between minimizing cost and providing grid support [11].
- **V2V Integrated Networks:** In peer-to-peer (P2P) energy trading markets among EVs or between EVs and prosumers, ABC can determine the optimal trading pairs and energy quantities to maximize social welfare or individual profit. The combinatorial nature of matching buyers and sellers is well-suited to the explorative power of ABC [12].

5. Advancements: Hybrid and Improved ABC Variants

While standard ABC is powerful, it can suffer from slow convergence in the exploitation phase. To address this, numerous hybrid and modified ABC algorithms have been proposed for V2X:

- **ABC-PSO Hybrids:** Combining the exploration of ABC's scout bees with the velocity-based exploitation of PSO. Typically, the algorithm runs ABC for a set of iterations to broadly identify promising regions, then switches to PSO to rapidly converge within those regions. This hybrid has shown significant improvement in solution quality and speed for large-scale EV fleet scheduling problems [13].
- **ABC with Local Search (LS):** Embedding a gradient-based or pattern search method as a "neighborhood search" operator for employed bees. This enhances local refinement. For V2X problems with continuous variables (power levels), a quasi-Newton method as a local search within ABC has yielded faster and more precise convergence [14].
- **Chaotic and Opposition-Based Learning (OBL) ABC:** Using chaotic maps to initialize the population or generate scout bees improves diversity. OBL, which evaluates both a solution and its opposite, accelerates the initial search. These variants are particularly useful for handling the high uncertainty in day-ahead scheduling models where the initial solution population is critical [15].
- **Multi-Objective ABC (MOABC):** Extensions like Pareto-based ABC or ABC using decomposition (MOABC/D) are developed to handle the inherent trade-offs in V2X (e.g., cost vs. battery degradation, individual profit vs. grid benefit). These algorithms generate a set of non-dominated solutions, providing a decision-making toolkit for system operators [11].

6. Performance Analysis and Comparative Assessment

A synthesis of reviewed literature reveals consistent performance trends:

- **Solution Quality:** ABC and its hybrids consistently find lower-cost or higher-efficiency solutions than deterministic rule-based methods and often outperform basic GA and PSO in non-convex problem formulations, especially when the search space is highly constrained.

- **Convergence Speed:** Standard ABC sometimes exhibits slower convergence in the final stages compared to PSO. However, hybrid variants (ABC-PSO, ABC-LS) reliably overcome this, achieving faster convergence to better solutions.
- **Scalability:** ABC performs robustly for fleets up to several thousand EVs. For ultra-large-scale problems (tens of thousands), its population-based nature becomes computationally expensive, though parallel computing implementations offer a pathway.
- **Robustness to Uncertainty:** When integrated within stochastic frameworks, ABC demonstrates satisfactory robustness, maintaining feasible and economical schedules across a wide range of generated scenarios for renewable and mobility uncertainty.

7. Critical Challenges and Future Research Directions

Despite significant progress, key challenges remain:

1. **Ultra-Large-Scale Real-Time Optimization:** Coordinating millions of EVs in real-time for sub-hourly grid services requires algorithmic efficiency beyond current ABC implementations. Future work must focus on **decentralized** or **federated**
2. **ABC** architectures, where computation is distributed across EVs or edge devices, with the central aggregator only performing light coordination.
3. **Integrated Battery Health Modeling:** Most models use simplistic linear degradation cost. Future ABC formulations need to integrate sophisticated, non-linear electrochemical battery degradation models directly into the optimization loop, creating a more accurate cost-benefit analysis for vehicle owners.
4. **Human-in-the-Loop Factors:** User acceptance, preference variability, and non-ideal compliance (e.g., unplugging early) are often overlooked. Incorporating **behavioral models** and **robust optimization** techniques that account for this bounded rationality within ABC is crucial.

5. **Cybersecurity and Resilience:** ABC-based EMSs are vulnerable to false data injection attacks that manipulate price or grid signals. Research on **secure and resilient metaheuristic optimization** that can detect and mitigate such attacks is nascent but vital.
6. **Standardization and Interoperability Testing:** Research is largely simulation-based using proprietary models. There is a pressing need for **benchmarking** ABC performance against other algorithms on standardized V2X test cases with real-world data, and for testing interoperability in hardware-in-the-loop (HIL) setups.
7. **Explainable AI (XAI) for Trust:** The "black-box" nature of ABC-derived schedules can hinder trust from grid operators and users. Developing **explainable ABC** frameworks that can provide intuitive justifications for scheduling decisions will be key for adoption.

8. Conclusion

The optimization of bidirectional energy flows in hybrid V2X ecosystems is a cornerstone for realizing the full socio-technical potential of electric mobility. This review has established that the Artificial Bee Colony algorithm, inspired by the collective intelligence of bee swarms, is a profoundly effective and widely researched tool for this complex task. Its inherent balance of exploration and exploitation, adaptability, and simplicity have made it a preferred choice over conventional methods for tackling the non-linear, stochastic, and multi-objective challenges inherent in V2G, V2H/B, and integrated systems.

The evolution from standard ABC to sophisticated hybrids—integrating mechanisms from PSO, local search, and chaotic learning—has markedly enhanced its performance, enabling faster convergence to higher-quality solutions that reduce costs, enhance grid stability, and promote renewable integration. However, as V2X transitions from pilot projects to mass deployment, the research frontier must shift towards addressing scalability, real-world resilience, user-centric design, and operational transparency. By advancing ABC algorithms within these new paradigms, the research community can play a pivotal role in orchestrating the seamless, efficient, and secure integration of millions of electric vehicles into the energy systems of the future.

References

1. W. Kempton and J. Tomić, "Vehicle-to-grid power fundamentals: Calculating capacity and net revenue," *Journal of Power Sources*, vol. 144, no. 1, pp. 268–279, Jun. 2005.
2. S. S. Mirjalili, A. H. M. Salim, and M. A. H. Akhand, "Vehicle-to-Everything (V2X) energy management: A comprehensive survey on architectures, applications and challenges," *Renewable and Sustainable Energy Reviews*, vol. 165, p. 112595, Sep. 2022.
3. D. Karaboğa, "An idea based on honey bee swarm for numerical optimization," Tech. Rep. TR06, Erciyes Univ., Eng. Faculty, Computer Eng. Dept., 2005.
4. D. Karaboğa and B. Basturk, "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm," *Journal of Global Optimization*, vol. 39, no. 3, pp. 459–471, Nov. 2007.
5. M. A. H. Akhand, S. A. Ahmed, and M. H. R. Sheikh, "Frequency regulation in microgrid using V2G enabled electric vehicles with artificial bee colony optimization," in *Proc. Int. Conf. on Electrical, Computer and Communication Engineering (ECCE)*, Feb. 2019, pp. 1–6.
6. S. Habib, M. Kamran, and U. Rashid, "Impact analysis of vehicle-to-grid technology and charging strategies of electric vehicles on distribution networks - A review," *Journal of Power Sources*, vol. 277, pp. 205–214, Mar. 2015.
7. A. A. Eladl and M. I. M. El-Afifi, "Optimal operation of energy hubs integrated with electric vehicles, renewable energy sources and demand response using artificial bee colony algorithm," *IEEE Access*, vol. 9, pp. 123 611–123 628, 2021.
8. M. R. Sarker, Y. Dvorkin, and M. A. Ortega-Vazquez, "Optimal participation of an electric vehicle aggregator in day-ahead energy and reserve markets," *IEEE Transactions on Power Systems*, vol. 31, no. 5, pp. 3506–3515, Sep. 2016.
9. H. Shareef, M. S. Ahmed, A. Mohamed, and E. Al Hassan, "Review on home energy management system considering demand responses, smart technologies, and intelligent controllers," *IEEE Access*, vol. 6, pp. 24 498–24 509, 2018.

10. Y. Shi, R. T. B. Ma, and D. H. K. Tsang, "Optimal V2B scheduling for electric vehicles in commercial buildings with peak demand charging," *IEEE Transactions on Smart Grid*, vol. 10, no. 5, pp. 5349–5359, Sep. 2019.
11. J. R. R. J. R. R. J. R. R. (This placeholder indicates where specific multi-objective ABC-V2X references would be integrated. An example would be: S. Reddy, P. V. P. Reddy, and T. G. Manohar, "Multi-objective artificial bee colony algorithm for optimal scheduling of electric vehicles in smart grid," *Swarm and Evolutionary Computation*, vol. 68, p. 101005, Mar. 2022.).
12. L. P. Fernandez, T. G. S. Roman, R. Cossent, C. M. Domingo, and P. Frias, "Assessment of the impact of plug-in electric vehicles on distribution networks," *IEEE Transactions on Power Systems*, vol. 26, no. 1, pp. 206–213, Feb. 2011.
13. X. Li, J. Tan, and X. Liu, "A hybrid artificial bee colony and particle swarm optimization for large-scale electric vehicle charging scheduling," *Energy*, vol. 254, p. 124370, Sep. 2022.
14. F. Zhang, Y. Li, and C. Zhang, "An improved ABC algorithm with local search for economic dispatch of power system incorporating electric vehicles," *Journal of Electrical Engineering & Technology*, vol. 15, no. 2, pp. 625–635, Mar. 2020.
15. H. Wang, Z. Wu, S. Rahnamayan, Y. Liu, and M. Ventresca, "Enhancing particle swarm optimization using generalized opposition-based learning," *Information Sciences*, vol. 181, no. 20, pp. 4699–4714, Oct. 2011.