An Ant Colony Algorithm for HRES Size and Configuration Optimisation

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***Abstract*—An Ant colony algorithm (ACO) is proposed for hybrid renewable energy system size and configuration optimisation using continuous search space approach. In the proposed algorithm the pheromone distribution across search space is determined by gaussian distribution, and the probabilistic path selection is performed based on pheromone deposit value via roulette wheel principle. The ACO algorithm is implemented in the software tool MOHRES and three case studies are conducted to optimise the size and configuration of standalone hybrid renewable energy system derived from the full configuration wind-PV-battery-diesel-FC Electrolyser system. To evaluate the performance of the proposed ACO, the optimum solutions are compared with the solutions obtained by the genetic algorithm (GA) optimisation algorithm implemented in MOHRES.**

Keywords— hybrid renewable energy system, size and configuration optimisation, ant colony algorithm, MOHRES

I. Introduction

Due to technical and economic problems in grid extension to isolated locations, fossil fuel-based systems are used to generate electricity. These systems contribute to global warming problem and impact local air quality. Renewable energy sources like solar and wind are alternative solution providing that the system used is competitive with the conventional systems. Optimised hybrid renewable energy systems (HRES) are considered as effective, economic, reliable, and environmentally friendly energy systems [1].

HRES size optimisation is classified as a combinatorial optimisation problem owing to different electrical components involved in the system and the characteristic variations of energy sources [2-6]. The level of the complexity of the problem depends on how the problem has been formulated in terms of the objective, constraints, and the nature of design variable involved. As the level of complexity of the problem increases, the optimal solution cannot be obtained or always guaranteed by classical methods such as heuristic algorithms within reasonable amount of time. On the other hand, meta-heuristic optimisation techniques are proven to be very effective for finding optimal solutions in a reasonable time irrespective of the level of the complexity of the problem [7, 8].

In this article, ant colony-based algorithm is proposed to optimised size and configuration of standalone PV-Wind-Battery-Diesel-Hydrogen system using continues design space approach. The proposed search algorithm is implemented in MOHRES and tested by conducting three case studies. To evaluate the quality of the solution obtained by the proposed algorithm, they are compared with MOHRES's genetic algorithm solutions.

II. Problem Formulation

The There are six electrical components available for the size and configuration optimisation of HRES: the primary power supplies (wind Turbines and solar PV panels), auxiliary power supply (diesel generator), electrical storage system (battery), and hydrogen-based energy storage system (Fuel cells and water electrolysers).

The power output of wind turbine can be calculated as the following:

$$P_{WT} = \frac{1}{2}\pi\rho {V_{wind}}^3 R_{WT}^2 C_p \eta_{EG} \tag{1}$$

where, ρ is the air density, V_{wind} is the wind velocity, η_{EG} is the overall efficiency of the electrical components and gearbox of the wind turbine, R_{WT} is the rotor radius which determines the size of wind turbine in (m), and C_p is the power coefficient and calculated using the model proposed in [9].

PV panel power output is calculated by the following:

$$P_{PV} = I A_{PV} \eta_{PV} \tag{2}$$

where, I is solar irradiance, A_{PV} is the total area of PV panels and its size parameter in (m^2), and η_{PV} is the overall efficiency.

The size of the battery power bank is calculated by the total battery capacity in (Ah) with a unit voltage of (24 V). The mathematical models of charging and discharging process used in this work is presented in [10]. The size of diesel generator, fuel cell, and water electrolyser are based on their nominal power in (W) [10-12].

Therefore, the design vector $\vec{X}$ which contains all size parameters of HRES components: wind turbine rotor radius (R_{WT}), PV panel area (A_{PV},), Battery power bank capacity (C_B), diesel generator nominal power ($P_{D,nom}$), fuel cell nominal power ($P_{fc,nom}$), and water electrolyser nominal power ($P_{elec,,nom}$). The design vector can be express mathematically as the following:

$$\vec{X} = \{R_{WT}, A_{PV}, C_B, P_{D,nom}, P_{fc,nom}, P_{elec,,nom}\} \tag{3}$$

The candidate HRES is evaluated by some economic ($\vec{Y}_1$), technical ($\vec{Y}_2$), and environmental ($\vec{Y}_3$) measures as follows using the mathematical models proposed in [9, 10, 13-15]:

$$\vec{Y}_1(\vec{X}) = \{TLSC, LCE\} \tag{4}$$

$$\vec{Y}_2(\vec{X}) = \{U_t, MTBF, E_{excess}\} \quad (5)$$

$$\vec{Y}_3(\vec{X}) = \{CO_2, p\} \quad (6)$$

where, $TLSC$, LCE, and $MTBF$ stand for total lifespan cost, levelised cost of energy, and mean time between failures respectively, U_t is total unmet load, P_{excess} is net excess energy, CO_2 is carbon dioxide emissions, p is renewable energy penetration rate.

Now, the optimisation problem can be formulated using equations (3) to (6) as the following:

$$min/max\, y_j\, ;\; y_j \in \vec{Y} \quad (7)$$

$$s.t.$$

$$\vec{Y}_a \leq \vec{Y}_i \leq \vec{Y}_b;\;\; \vec{Y}_i \subseteq \vec{Y} - \{Y_j\} \quad (8)$$

$$\vec{Y} = \vec{Y}_1 \cup \vec{Y}_2 \cup \vec{Y}_3 \quad (9)$$

$$\vec{X}_l \leq \vec{X} \leq \vec{X}_u \quad (10)$$

where, Y_j is a desired objective of optimization, one of system quality parameters of vector $\vec{Y}$, subjected to some constraints $\vec{Y}_i$, with the design space limits $\vec{X}_u$ and $\vec{X}_l$ (i.e. the upper and lower allowable size of components respectively).

III. Energy Dispatch strategy

This section explains the flow of energy model used for each candidate system obtained. The components of a candidate HRES generated by the algorithm used to utilised renewable energy (i.e. solar and /or wind) given by the meteorological data, such as the data given in Fig. 1 and Fig. 2, to satisfies a given demand load (Fig. 3).

Due to intermittent nature of solar irradiance and wind speed, the operation duration can be divided into two categories: energy surplus periods and energy deficit periods. During energy surplus periods, the excess energy is stored in the battery bank till fully charged. Then, hydrogen is generated using water electrolyser to full capacity. After that, any further excess energy available is dumped to maintain the power balance of the system.

When the renewable power produced by the primary supply is less than the demand load (energy deficit period), energy is drawn from the battery bank first then hydrogen storage via fuel cell. If the two storage systems failed to satisfy the demand load, diesel generator is dispatched at its nominal power where its excess energy whenever available is stored in the available storage systems.

IV. Ant colony optimisation algorithm

Ant colony algorithm was introduced by Dorigo initially to solve the classical optimisation problem (travel salesman problem) [16]. While the search method can simply be applied to discrete domain optimisation problem, extending the algorithm to continuous domain problem is open ended approach.

In this work, the proposed optimisation algorithm used to solve the HRES size and configuration optimisation problem is based on Gaussian distribution for new solution generation and roulette wheel principle for the probabilistic path selection.

Ant colony-based optimisation algorithm do the following:

- Step 1: Generate number of feasible solution equal to the number of ants n. The pheromone distribution is assumed to be normally distributed in the search space (pheromone initiation).
- Step 2: Calculate the cost of k^{th} solution as the following:

$$C_k = f(y_j) \quad (11)$$

- Step 3: Calculate the pheromone values of k^{th} solution by the following:

$$\tau_k = \begin{Bmatrix} C & ; max\ C \\ \frac{1}{C} & ; min\ C \end{Bmatrix} \quad (12)$$

- Step 4: Calculate the probability associated to each solution by the following:

$$p_k = \frac{\tau_k}{\sum_{k=1}^{N} \tau_k} \quad (13)$$

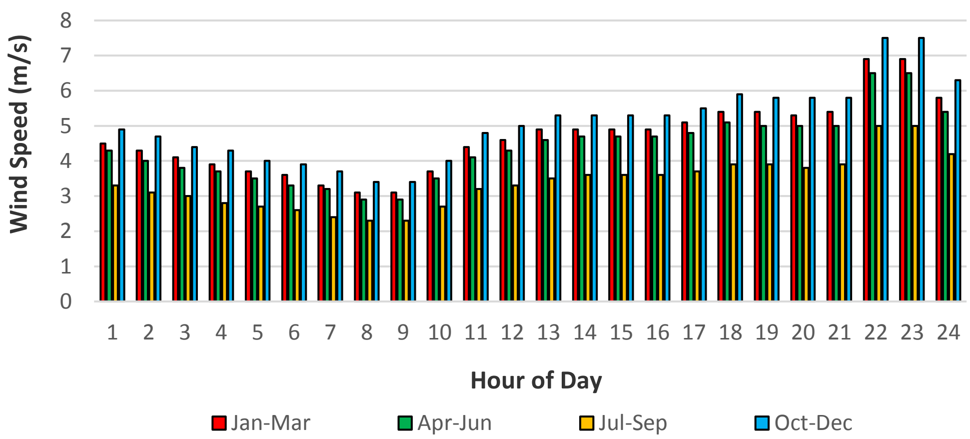

Fig. 1. Hourly averaged wind speed of typical seasonal days.

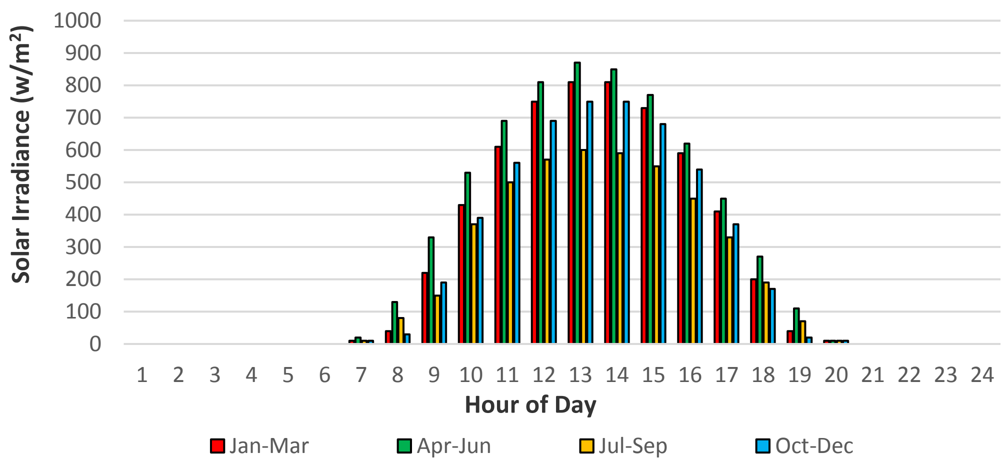

Fig. 2. Hourly averaged solar irradiance of typical seasonal days.

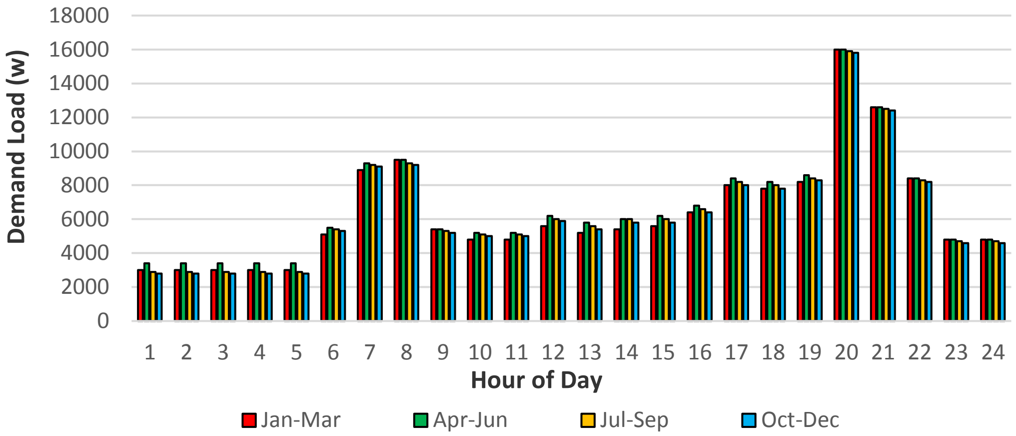

Fig. 3. Hourly averaged demand load of typical seasonal day.

where, p_k is the probability of choosing $\vec{X}_k$.

- Step 5: Update the heuristic set S of the colony as follows:

$$\overrightarrow{s_k} = (\vec{X}_k, p_k)\ ;\ k = 1, \dots., N \quad (14)$$

$$S = [\vec{s}\,]_{Nxn+1} \quad (15)$$

where, N is the number of feasible solution and n is size of $\vec{X}$.

- Step 6: If termination condition is met, stop.
- Step 7: Apply pheromone evaporation:

$$\tau_k = \begin{Bmatrix} \tau_k\ ;\ \tau_k > \tau_{m+1} \\ 0\ ;\ \tau_k \le \tau_{m+1} \end{Bmatrix} ;\ \tau_{m+1} < \tau_i\ ;\ i = 1, \dots, m \quad (16)$$

- Step 8: Select $\overrightarrow{s_k}$ based on p_k.
- Step 9: Generate the new solution elements x_{ik} for $i = 1, \dots, n$ based on Gaussian distribution as following:

$$\mu_{ik} = s_{ik} \quad (17)$$

$$\sigma_{ik} = \sqrt{\frac{\sum_{k=1}^{N}(s_{ik} - \mu_{ik})^2}{N}} \quad (18)$$

$$f(x_{ik}, \mu_{ik}, \sigma_{ik}) = \frac{1}{\sigma_{ik}\sqrt{2\pi}} e^{\frac{-(x_{ik}-\mu_{ik})^2}{2\sigma_{ik}^2}} \quad (19)$$

- Step 10: evaluate the new generated solutions $\vec{X}_k$ if feasible go back to step 2.

V. Case Studies

There are three scenarios presented in this section where each optimised three times with different number of agents to test the sensitivity of the proposed algorithm towards the number of agents used.

Some technical and economic parameters are assumed constant during HRES lifespan of 20 years of operation. They are explicitly listed below.

The overall efficiencies of wind turbine, PV panel, fuel cell, and electrolyser are fixed at 0.9, 0.14, 0.47, and 0.74, respectively. The charging efficiency of the battery is 0.9 whereas its discharging efficiency is assumed to be higher by 0.05. The battery self-discharge rate is 0.002.

The capital cost of wind turbine used in the economic assessment is \$480 per meter squared of rotor area, the cost of one meter squared of PV panel is \$840, and the cost of 40 Ah battery unit capacity is \$1.5. The capital costs of diesel, fuel cell, and electrolyser are 0.4, 4.08, and 2 US dollars per unit nominal power, respectively. The O&M costs are calculated by a fraction of the capital costs where 0.03 is assumed for the wind turbine, 0.01 is for the PV panel and the battery,0.15 is for the diesel generator, and 0.1 is for the fuel cell and the electrolyser. Likewise, the installation costs for wind turbine and PV panel, respectively, are equal to 0.2, and 0.4 of their capital costs. The rest of the components are assumed to be plug and play models (i.e. there are no installation costs associated with battery, diesel generator, fuel cell, and electrolyser). Also, the replacement costs are considered in these case studies. As a matter of fact, the replacement costs depend on the nominal life of each component in the system. Wind turbine and PV panel lifespan are assumed 25 years. The lifespan of the battery is 4 years at 0.5 DoD. The nominal life of diesel generator, fuel cell, and the electrolyser are assumed based on hours of operation which are 10000, 5000, 60000 hours, respectively. The price of a litre of diesel is \$1. The real discount rate used in this study is 0.04. These parameters mentioned above are used in all case studies presented in this work.

The first case (CS1) is performed to optimised HRES for the local solar irradiance and wind speed profiles given in Fig. 1 and Fig. 2 respectively to serve the demand load given in Fig. 3. The second scenario (CS2) assumes that the solar irradiance is lower than the given values by 50%. This assumption tests the response of the optimisation algorithm towards the change of input data. In the last case (CS3) more constraints are imposed on the optimisation process. The three optimisation cases are summarised in TABLE I, TABLE II, and TABLE III.

The results of the optimisation using the proposed ACO and MOHRES's GA are presented in TABLE IV, and TABLE V, respectively.

The optimum configuration for CS1 conditions is PV-battery providing that the costs of PV system is the lowest among all power suppliers. Due to limitations in solar energy resources imposed by the designer, hybrid PV-diesel-battery system is the optimum solution complies with the reliability constraint. With two reliability and environmental constraints involved, Wind-PV-Diesel-Battery system is the optimum system configuration. Hydrogen-based storage components are most expensive components and not expected to be within the optimum solutions since the seasonal demand variation is very small and battery self-discharge rate is acceptable compared with Hydrogen-based storage components' costs.

TABLE I. OPTIMISATION FORMULATION SUMMARY OF CS1.

Case Study		Problem Formulation [a]	Design variables	Number of agents
CS1	1	$\min LCE$ s. t. $U_t = 0$	$\vec{X}_l = \{0,0,0,0,0,0\}$ $\vec{X}_u = \{R_{WT}^u, A_{PV}^u, n_B^u, P_{D,nom}^u, P_{FC,nom}^u, P_{EL,nom}^u\}$ * Wind speed, solar irradiance, , and demand load as given in Fig. 1, Fig. 2, and Fig. 3, respectively.	$m = 20$
	2			$m = 50$
	3			$m = 100$

[a] maximum iteration = 100. Termination condition: $C_{av} - C_{min}$ = 0,0001. Maximum size vector is calculated based on demand peak.

TABLE II. OPTIMISATION FORMULATION SUMMARY OF CS2.

Case Study		Problem Formulation [b]	Design variables	Number of agents
CS2	1	$\min LCE$ s. t. $U_t = 0$	$\vec{X}_l = \{0,0,0,0,0,0\}$ $\vec{X}_u = \{R_{WT}^u, A_{PV}^u, n_B^u, P_{D,nom}^u, P_{FC,nom}^u, P_{EL,nom}^u\}$ *50% less Solar irradiance than given in Fig. 2. *Wind speed and demand load as given in Fig. 1 and Fig. 3, respectively.	$m = 20$
	2			$m = 50$
	3			$m = 100$

[b] maximum iteration = 100. Termination condition: $C_{av} - C_{min}$ = 0,0001. Maximum size vector is calculated based on demand peak.

TABLE III. OPTIMISATION FORMULATION SUMMARY OF CS3.

Case Study		Problem Formulation [c]	Design variables	Number of agents
CS3	1	$\min LCE$ s. t. $U_t = 0$ $CO_2 \leq 1000$ kg	$\vec{X}_l = \{0,0,0,0,0,0\}$ $\vec{X}_u = \{R_{WT}^u, A_{PV}^u, n_B^u, P_{D,nom}^u, P_{FC,nom}^u, P_{EL,nom}^u\}$ *50% less Solar irradiance than given in Fig. 2. *Wind speed and demand load as given in Fig. 1 and Fig. 3, respectively.	$m = 20$
	2			$m = 50$
	3			$m = 100$

[c] maximum iteration = 100. Termination condition: $C_{av} - C_{min}$ = 0,0001. Maximum size vector is calculated based on demand peak.

TABLE IV. OPTIMISATION RESULTS FOR CASE STUDY CS1, CS2, AND CS3 USING ACO.

	$\vec{X}$						$\vec{Y}$						
Case Study	R_{WT} (m)	A_{PV} (m^2)	C_B (Ah)	$P_{D,nom}$ (W)	$P_{FC,nom}$ (W)	$P_{EL,nom}$ (W)	$TLSC$ (\$)	LCE $(¢/kWh)$	U_t (kW)	$MTBF$ (h)	E_{excess} (kWh)	CO_2 (kg)	p (%)
CS1.1	0	281	8320	0	0	0	174740	22.77	0	8760.0	13829	0	138.17
CS1.2	0	280	8320	0	0	0	174360	22.72	0	8760.0	13608	0	137.68
CS1.3	0	280	8320	0	0	0	174360	22.72	0	8760.0	13608	0	137.68
CS2.1	0	443	8160	7800	0	0	278720	36.32	0	8760.0	3163	3135	108.92
CS2.2	0	448	8160	6800	0	0	276390	36.02	0	8760.0	3586	2733	110.15
CS2.3	0	444	8400	3600	0	0	267760	34.89	0	8760.0	3041	2028	109.16
CS3.1	3.0	448	6880	3100	0	0	308890	40.25	0	8760.0	11581	750	127.99
CS3.2	2.8	448	6960	5000	0	0	307590	40.08	0	8760.0	10169	807	125.54
CS3.3	3.1	448	6800	3500	0	0	311700	40.62	0	8760.0	12384	565	129.29

TABLE V. OPTIMISATION RESULTS FOR CASE STUDY CS1, CS2, AND CS3 USING GA[*].

	$\vec{X}$						$\vec{Y}$						
Case Study	R_{WT} (m)	A_{PV} (m^2)	C_B (Ah)	$P_{D,nom}$ (W)	$P_{FC,nom}$ (W)	$P_{EL,nom}$ (W)	$TLSC$ (\$)	LCE $(¢/kWh)$	U_t (kW)	$MTBF$ (h)	E_{excess} (kW)	CO_2 (kg)	p (%)
CS1.3	0	284	11360	0	0	0	183090	23.85	0	8760.0	13587	0	139.0
CS2.3	0	447	9360	7100	0	0	282900	36.87	0	8760.0	1871	2292	109.90
CS3.3	3.5	439	6400	4900	0	0	324240	42.25	0	8760.0	14641	791	132.80

[*] The crossover and mutation parameters are 0,3 and 0,9 respectively Population size = 100. Number of generations = 100.

The small variation in the size of the system is due to the stochastic nature of search process and round up process involved in the simulation. However, these variances are not significant with respect to the objective function. The search performance of the proposed algorithm is shown in Fig.4.

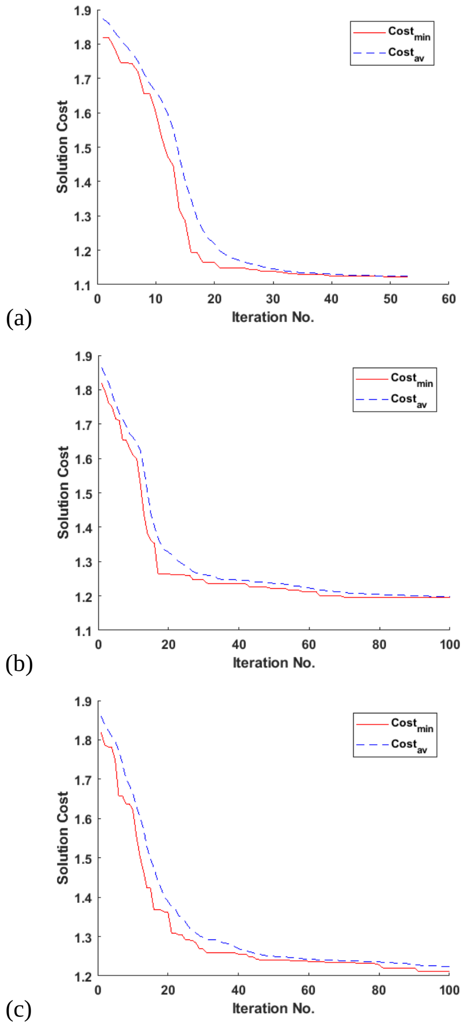

Fig. 4. Search performance of proposed ant colony algorithm of (a) CS1.1, (b) CS2.1, and (c) CS3.1.

VI. DISCUSSION

For the first case study scenario (CS1), the algorithm converges to the optimum solution before reaching the maximum iteration with no change with respect to number of agents increase. This is expected since PV system is considered the most economic system among all available power supply systems in this optimisation. In CS2, the maximum number of PV panels is insufficient to produce enough energy, the optimum solution is in another area in the design space where hybrid PV-Diesel system configuration exists. This is true since diesel generator is considered the second cheapest system. Due to CO2 emissions constraint in CS3, wind energy is utilised due to insufficient PV power and limitations in diesel generator power.

Although the algorithm is able to converge to the optimum configuration, it is not necessarily that it finds the optimum size of the system since the termination is caused by reaching maximum iteration allowable by the designer (see Fig. 4.b and Fig. 4.c) which does not guarantee that the algorithm convergence is mature. In other words, although the algorithm is less sensitive to number of agent (m), a greater number of iterations are required as the optimisation problem complexity increases.

Comparing the results with those obtained by GA one may argue that better solutions can be obtained by GA by tuning the search parameters population size, number of generations, and crossover and mutation probabilities. While true, the results show that the performance of ACO algorithm is at least comparable with that of GA with less user intervention and burden of tuning search parameters.

VII. CONCLUSION

Optimum size and configuration of HRES are obtained by the proposed ACO algorithm. The sensitivity towards the number of agents used in the optimisation is insignificant. The search performance of the proposed algorithm shows promising results with minimal user intervention.

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