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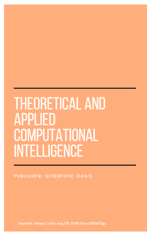

Sunspot Occurrence Forecasting With Metaheuristic Optimized Recurrent Neural Networks

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ABSTRACT

Solar activity plays an important role when considering terrestrial communication. Solar activity plays an even more important role when working with communication systems relying on artificial satellites. Electromagnetic emissions, known as solar flares, can disrupt communications and damage important infrastructure. However, as powerful solar flares are often preceded by observable occurrences of sunspots, a robust system prognosis system can be leveraged to help improve chances of minimizing damage to infrastructure. This work explored the potential of recurrent neural networks coupled with an introduced modified metaheuristic algorithm to tackle the increasingly pressing challenge of forecasting solar activity based on historical data. Due to the heavy reliance of neural networks on proper parameter selections as well as adequate architectural structure, the introduced optimizer is leveraged for the optimization of these control parameters. The proposed approach is evaluated on a real-world dataset that is publicly available. The outcomes are compared to several well-established optimization metaheuristics, and the outcomes show great promise for tackling this increasingly important topic as we head into the peak of the current solar cycle.

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1. Introduction

Weather conditions in space, especially those near Earth, have been known to have an influence on telecommunications, satellites, aircraft, and spacecraft functioning [1, 2]. Because of this, a field of research focusing on space climate is becoming more popular. Unsurprisingly, the Sun is one of the bigger contributors to the solar system's weather conditions because of its varying emissions of energy, sunspots, and solar flares. Solar flares are often followed by significant emissions of electromagnetic energy, and whilst most of these are minor and partially mediated by Earth's magnetic field, they may cause geomagnetic storms that affect, as mentioned, telecommunications, satellites, and such [3, 4]. In the case of more severe interference, radio blackouts and damage to ground communication and infrastructure may occur. Since the flares tend to be preceded by sunspots, a valid way of predicting flares is actually by predicting sunspots.

To deal with and prevent these unwanted consequences, a way of predicting solar events using an accurate data-driven system is needed. The solar magnetic cycle refers to a well-known pattern of solar events almost periodically happening every 11 years [5]. The high period of the cycle is of particular interest since the emissions are more frequent during it. Therefore weather conditions have a bigger influence on Earth. Sunspots, solar flares, and electromagnetic emissions have been observed increasingly during the high period. Solar data processing is necessary to be done quickly since the effect of flares on Earth can be felt within minutes [6]. Reliably and accurately predicting the solar cycle is still a challenge in astrophysics, while the solution could also be useful to the field of magneto-hydrodynamics. Forecasting solar flares would, of course, enable preventative measures to be taken and sensitive infrastructure preserved.

Artificial intelligence (AI) is one of the more promising approaches to forecasting solar flares and their effects on Earth. AI has been successfully utilized for many realistic problems due to advancements in computational power and increased research in the field. Since sunspots are a common precursor of solar flares, they could be used to forecast future solar events [7]. AI algorithms most suited for this task would be those using temporal data, as solar activity tends to be periodic. Defining the task as a time series forecasting problem would allow for optimal and accurate predictions via AI algorithms serving as early warnings for the events.

In order to properly implement AI to predict solar flares, enough data is required to train and evaluate the algorithms. Since many scientific facilities monitor and document solar weather, this issue is resolved. A different challenge is posed by hyperparameter tuning [8]. Modern algorithms tend to do generally well on broader tasks. However, they require extra adjustment to suit particular tasks better. The hyperparameter selection process tends to be an NP-hard problem since the values include both discreet and continuous data. With this in mind, hyperparameter tuning should be done through automatic methods to ensure the truly optimal functioning of the algorithm. In line with the "No free lunch" (NFL) [9] theorem, no single solution is best for all presented problems. Testing of multiple possible solutions is thus needed to find the best-suited one for the particular problem.

One of the promising options for dealing with NP-hard problems such as hyperparameter tuning is metaheuristic algorithms [10]. They present a category of algorithms using advanced search methods to attain the optimal solution from a search space without getting stuck on the local best solutions. Metaheuristic algorithms are based on groups of cooperative members often found in nature. Swarm intelligence is a subcategory of metaheuristic algorithms, implementing agent populations that are improved through each iteration until an optimal solution is found, making them an especially good candidate for tackling hyperparameter tuning. Because of this feature, swarm intelligence provides an optimal or near-enough solution while spending realistic computational resources and within reasonable time frames.

In this work, an approach based on time series forecasting that relies on RNN is applied to predict the number of upcoming sunspots. Additionally, a modified version of a well-known metaheuristic is introduced to help tune hyperparameter values and improve overall performance. The proposed methodology is evaluated on a real-world, publicly available dataset that spans an entire century of observations.

A brief summary of the scientific contributions of this work is as follows:

- A proposal for a time-series-based approach for predicting the number of occurring sunspots in upcoming months.
- An introduction of a modified version of a well-known optimization algorithm applied to hyperparameter tuning specifically for the needs of this work.
- The application of the introduced methodology to a real-world publicly available dataset to demonstrate and assess performance and viability.

This work has the following structure: in Section 2, previous relevant research is presented. The introduction and explanation of the modified metaheuristic algorithm can be found in Section 3. In Section 4, the utilized dataset, metrics for the evaluation of models, and experimental parameters are presented. The results of the conducted experiments are presented in Section 5. Lastly, Section 6 presents the conclusion of the work and future research plans and recommendations.

2. Related Works

Solar flares have recently gained additional attention in the scientific community considering their effect on Earth, leading to extensive documentation of these solar events. However, the knowledge and interest in them are not new, as they have been regularly observed since the XIX century, overall resulting in significant amounts of readily available data. As flares generally result from sunspots, sunspots are often used as markers for forecasting solar activity. Some of the contributors to the collected data are the National Solar Observatory (NSO) [11], ESAC Solar Observatory (Helios) [12], and the Wilcox Solar Observatory (WSO) [13].

Standard statistical methods were initially employed to analyze this abundance of data on solar events. However, they were found to be somewhat lacking in comparison to the novel deep learning methods approach. Techniques continue to develop inspired by the problem of accurately forecasting solar flares, more specifically, using sunspots.

Convolutional Neural Networks (CNNs) [14] are one of the tried and true ways for the classification of solar flares. Since they are designed with image recognition in mind, CNNs are a great fit for analyzing solar flare data and sunspots that preceded them [15]. They have also been successfully implemented in the prediction of solar events. Alongside CNNs, RNNs [16] have also achieved good prediction of solar flares thanks to their ability to model temporal dependencies. Considering the previously explained periodic nature of sunspots and solar flares, RNNs recognize the latent patterns of flare eruptions, therefore successfully predicting them based on available data. This has been shown in previous research where RNNs have predicted potential dangerous solar events well, providing timely warnings.

The use of the mentioned deep learning methods has made a significant mark on the research of solar events, providing crucial knowledge of their mechanisms and nature. Finding the optimal way to use deep learning for space weather forecasting is a prerogative considering its potential to minimize and even prevent damage to Earth's functioning and infrastructure.

2.1. Recurrent neural networks

Time series prediction serves as the driving force behind advancements in artificial neural networks (ANN) [17]. In contrast to the multilayer perceptron, the distinguishing feature of RNN lies in the introduction of delayed connections among the hidden units. These modifications enable the model to exhibit sensitivity towards temporal occurrences of extended duration. The application of RNNs has been widely recognized as a high-performing solution.

While retaining fundamental elements of a neural network, such as neurons and connections, RNNs possess the ability to iterate a particular operation for sequential inputs through the incorporation of recurrent connections. Consequently, RNNs possess a memory component that captures processed values and facilitates their utilization alongside future inputs. Given an input sequence $I = i_1, i_2, i_3, ..., i_T$, at each time step t, the network repeats the operation described by Equation (1).

$$\begin{bmatrix} \hat{o}_t \\ h_t \end{bmatrix} = \phi_W(i_t, h_{t-1}) \tag{1}$$

within the given context, $\hat{o}t$ and h_t denote the output and hidden state at time t, respectively. Additionally, ϕ_W symbolizes a neural network characterized by a weighted network W. These networks take into account the t-th input i_t along with the preceding hidden state $ht - 1$ as inputs. The architecture of an RNN is highly adaptable, making it well-suited for tackling a diverse range of intricate problems.

2.2. Metaheuristic Optimization

As the current AI algorithms get more complex, a need arises for better optimization techniques. With the control parameters becoming more numerous, the process of implementation becomes more accurate but also more dependent on finding optimal values. Metaheuristic algorithms address this pending problem, with swarm intelligence being a particularly useful subcategory.

These algorithms mimic the mating, foraging, and hunting behaviors of various living beings via mathematical models that reflect the nature of these behaviors. Often used swarm intelligence algorithms include Artificial Bee Colony (ABC) [18], Firefly Algorithm (FA) [19], Bat Algorithm (BA) [20], and the recent Reptile Search Algorithm (RSA) [21], as well as some inspired by more abstract concepts such as the Sine Cosine Algorithm (SCA) [22], Particle Swarm Optimizer (PSO) [23], and the notably powerful COLSHADE [24] Optimization Algorithm. The concept of evolution has also been utilized in the particularly efficient Genetic Algorithm (GA) [25].

Because of their outstanding performance regarding general optimization, metaheuristic algorithms have been successfully implemented in many different fields. Some of them include computer system security [26], addressing complex challenges in emerging industries [27], application in environmental sciences [28]. More specifically, metaheuristics have achieved great results in time series forecasting [29, 30], suggesting they may be a viable option for time series prognosis of sunspots.

3. Methods

The following section presents the original metaheuristic algorithm and highlights the mechanisms used for the optimization. This is then followed by a brief discussion on how the algorithms see improvement and the mechanisms incorporated into the modified version of the algorithm.

3.1. Original SCA

The optimization process of the SCA [22] begins with a collection of random solutions as a starting point. These solutions are then enhanced using a set of rules that form the basis of an optimization approach. The effectiveness of this approach is evaluated by an objective function. Both stages of the optimization process, namely exploration, and exploitation, are equally important.

During the exploration stage, the optimization algorithm combines the random solutions with a high degree of unpredictability, with the goal of identifying the most promising areas within the search space. However, as the process transitions to the exploitation phase, the random solutions undergo progressive modifications, and the level of random fluctuations decreases significantly compared to the exploration phase. In this study, the following equations for updating positions are proposed for both stages:

$$X_i^{t+1} = X_i^t + r1 \times \sin(r2) \times |r3P_i^t - X_i^t| \tag{2}$$

$$X_i^{t+1} = X_i^t + r1 \times \cos(r2) \times |r3P_i^t - X_{i\,i}^t| \tag{3}$$

where the position of the current solution in the i-th dimension at the t-th iteration is denoted as X_i^t. Random values $r1$, $r2$, and $r3$ are used, and P_i represents the position of the destination point in the i-th dimension. The absolute value is denoted by $||$. The combination of these two equations is as follows:

$$X_i^{t+1} = \begin{cases} X_i^t + r1 \times \sin(r2) \times |r3P_i^t - X_i^t|, r4 < 0.5 \\ X_i^t + r1 \times \cos(r2) \times |r3P_i^t - X_{i\,i}^t|, r4 \geq 0.5 \end{cases} \tag{4}$$

where $r4$ is a random number in $[0, 1]$.

The SCA method incorporates four important parameters: $r1, r2, r3$, and $r4$. The parameter $r1$ determines the position regions during the optimization process. The parameter $r2$ determines the magnitude of movement. The parameter $r3$ controls the influence of an endpoint on solutions. Lastly, the parameter $r4$ is responsible for switching between the sine and cosine functions in Equation 4.

3.2 Modified SCA

While the SCA [22] optimizer demonstrates admirable performance, extensive experimentation as well as testing with standard CEC [31] functions suggests that further improvements are possible. As the SCA can, in certain executions, demonstrate less favorable performance caused by an excessive focus on less promising regions of the search space. This results in overall decreased quality of outcomes.

Fortunately, algorithm hybridization is a well-established approach for overcoming known deficiencies of optimization algorithms. This work incorporates the well-known FA search mechanism shown in Eq. 5 into the basic SCA [22] algorithm to overcome the observed lack of exploratory power.

$$X_i^{t+1} = X_i^t + \beta_0 \cdot e^{-\gamma r_{i,j}^2}(X_j^t - X_i^t) + \alpha^t(\kappa - 0.5) \tag{5}$$

where the randomization variable is defined as α, κ denotes the pseudo-random number taken from the Gaussian distribution. The range among individuals i and j is given by $r_{i,j}$. Variable γ defines the light propagating characteristic of the media, and β_0 is solution quality defined by the objective function outcomes.

The resulting low-level hybrid algorithms incorporate one additional mechanism in order to maintain good stability and allow both algorithms to contribute to the optimization process. The parameter ϕ is attached to each solution. In every iteration, a pseudo-random value in range $[0, 1]$ is generated for ϕ. If the value of ϕ for that solution is greater than 0.5 it utilizes the FA search mechanism. Otherwise, the standard SCA search is utilized. To encourage stability, this mechanism is only enabled following $\frac{1}{3}$ of the initial iterations.

Algorithm 1 Pseudocode of the HSA-SCA metaheuristics

```
Initialize a population of solution (X)
while t < maxIter do
  Evaluate fitness of population
  for Each agent in (X) do
    if t < maxIter/3 then
      Carry out SCA search
    else
      if rnd < sm then
        Carry out SCA search
      else
        Carry out FA search
return The current most fit individual established as the global optimum
```

4. Experimental Setup

This study utilizes historical sunspot data to forecast the number of future sunspots. The data is presented as a time series, and recurrent neural networks (RNNs) are employed to generate informed predictions three steps ahead. For evaluation purposes, a publicly available dataset [32] is utilized and can be publicly accessed [1].

A single-variable time series of observed sunspots spanning from 1789 to 2018, recorded on a monthly basis, is employed. The RNN model is trained to predict the number of sunspots for the next three months based on the preceding six months of data. The training process utilizes 70% of the dataset, 10% for validation, and the remaining 20% is used for testing and evaluating the model's performance.

During testing, metaheuristic algorithms have been tasked with selecting optimal parameters for RNN models in order to attain higher prediction accuracy. While there are many options for which parameters could be optimized, the selection for this work was narrowed down to a smaller subset that has the highest impact on model performance. Training parameters such as learning rate and number of training epochs have been tuned from respective ranges of $[0.0001, 0.01]$ and $[0.05, 0.2]$, respectively. Additionally, network architectures were optimized. The number of layers was selected from a range of $[1, 3]$, and the number of neurons in each layer was optimized from within a range of $[100, 300]$. Additionally, an early stopping condition of $\frac{epochs}{3}$ is used to help prevent overrating. Each constructed model was tasked with forecasting the number of sunspots three steps ahead based on six lags of historical data.

The evaluated metaheuristics include the introduced algorithm alongside the original SCA [22]. Several well-established algorithms have also been included to form a more complete comparison. The metaheuristics have all been subjected to identical test conditions and include the well-established GA [25], PSO [23], ABC [18], and FA [19]. Each algorithm was allocated a population of eight agents and allowed ten iterations to improve solution quality. Additionally, to account for the randomness inherent in metaheuristics algorithms, experiments were repeated through 30 independent runs.

[1] https://www.kaggle.com/datasets/robervalt/sunspots

To assess performance, several metrics are tracked during testing. These include: mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and lastly, the coefficient of determination (R^2) shown respectively in Eq. (6), Eq. (7), Eq. (8) and Eq. (9). In all equations, $\hat{y}_i$ represents the load forecast, y_i is the actual value, $\bar{y}$ is the arithmetic mean of actual values. Finally, N represents the total number of data samples.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2 \tag{6}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \tag{7}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i| \tag{8}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{9}$$

To further assess model performance, an additional metric is introduced. The Index of Agreement (IoA) is calculated as described in Eq. (10).

$$IoA = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(|y_p - \bar{y}| + |y_i - \bar{y}|)^2} \tag{10}$$

where $\hat{y}_i$ represents the forecast value, y_i is the actual value, $\bar{y}$ is the arithmetic mean of actual values.

5. Experimental Outcomes

Experimental outcomes of the objective function (MSE) for the 30 independent runs have been recorded, and the outcomes for the best and worst runs, alongside the median and mean outcomes, are shown in Table 2. Additionally, to demonstrate algorithms stability, standard deviation, and variance are given.

Table 2: Objective function overall outcomes

Method	Best	Worst	Mean	Median	Std	Var
RNN-MSCA	**0.004774**	**0.004935**	**0.004842**	**0.004843**	7.30E-05	5.30E-09
RNN-SCA	0.004899	0.004959	0.004940	0.004943	1.98E-05	3.93E-10
RNN-GA	0.004843	0.004956	0.004911	0.004910	4.10E-05	1.68E-09
RNN-PSO	0.004873	0.004952	0.004927	0.004930	2.88E-05	8.27E-10
RNN-ABC	0.004857	0.004936	0.004898	0.004895	2.74E-05	7.48E-10
RNN-FA	0.004905	0.004937	0.004922	0.004922	**1.17E-05**	**1.38E-10**

As it can be observed in Table 2, the introduced algorithm demonstrated remarkable optimization potential, with optimized models outperforming all competing algorithms. Additionally, it is worth noting that the FA, while not attuning to the optimal outcomes, demonstrated impressive stability. Stability

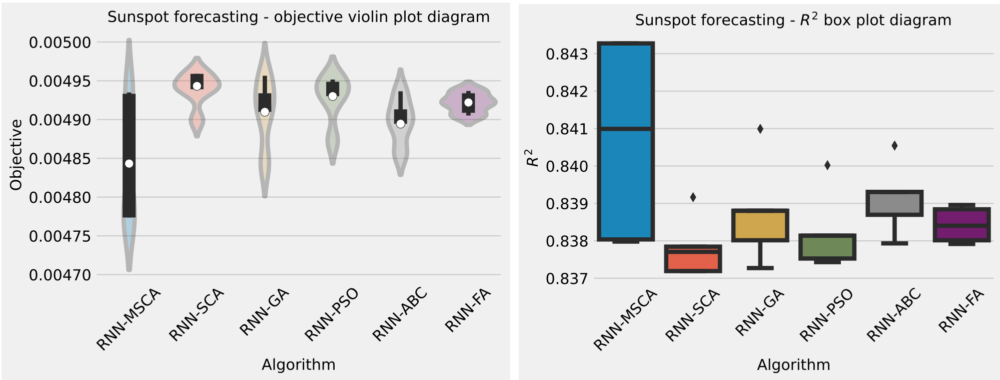

Figure 1: Objective and indicator function distribution graphs

comparisons between the tested algorithms can be seen in Figure 1 for both the objective and indicator functions.

Additionally, detailed overall metrics for the best-performing models generated by each metaheuristic are demonstrated in Table 3

Table 3: Overall evaluation metric outcomes for each optimization metaheuristic

Method	R^2	MAE	MSE	RMSE	IoA
RNN-MSCA	**0.843275**	20.359986	**756.928665**	**27.512337**	**0.955431**
RNN-SCA	0.839166	20.577399	776.776962	27.870719	0.954646
RNN-GA	0.840992	20.371043	767.957818	27.712052	0.954693
RNN-PSO	0.840021	20.696997	772.646707	27.796523	0.954500
RNN-ABC	0.840545	**20.260896**	770.114390	27.750935	0.954653
RNN-FA	0.838957	20.594586	777.782662	27.888755	0.954043

Once again, the introduced modified algorithm shows decent performance attaining the best outcomes across all metrics, coming in second to the ABC algorithm only for the MAE metric. These outcomes are further broken down in to by step comparisons between algorithms and shown in Table 4

Per step, outcomes indicated that the proposed algorithm attained the best results across all metrics when forecasting three steps ahead. Additionally, it attained admirable results for two steps ahead, being only outdone by the ABC metaheuristic for the MAE metric. Finally, an interesting observation can be made cornering one step ahead of forecasts, as the ABC algorithm demonstrated the best performance. This suggests that when making shorter-term forecasts, the ABC algorithm might be used to further improve the performance of the introduced algorithm in future works. This is, of course, in line with the NFL [9] theorem that states that no unified approach works the best for all possible cases across all metrics.

The improvements in convergence rates made by the alterations introduced to the original SCA can be seen in Figure 2 for the objective and in Figure 3 for the indicator function.

As it can be observed in both Figure 2 as well as Figure 3 there is a significant improvement compared to the original metaheuristics further enforcing the introduced alterations improve outcomes applied to this challenge.

Finally, to facilitate experiment repeatability, parameters selected by each metaheuristic for their respective best-performing RNN models are given in Tabel 5 for future research.

Table 4: Indicator function overall outcomes

Method	Metric	One step ahead	Two steps ahead	Three steps ahead
RNN-MSCA	R^2	0.839783	**0.845011**	**0.845031**
	MAE	20.454731	20.309227	**20.316001**
	MSE	773.792810	**748.544113**	**748.449073**
	RMSE	27.817132	**27.359534**	**27.357797**
	IoA	0.955419	**0.955827**	**0.955046**
RNN-SCA	R^2	0.837034	0.840250	0.840213
	MAE	20.580278	20.538985	20.612935
	MSE	787.072487	771.538215	771.720184
	RMSE	28.054812	27.776577	27.779852
	IoA	0.955025	0.954879	0.954034
RNN-GA	R^2	0.840141	0.841558	0.841276
	MAE	20.292095	20.379977	20.44106
	MSE	772.068105	765.220403	766.5849
	RMSE	27.786114	27.662617	27.687270
	IoA	0.955378	0.954748	0.953952
RNN-PSO	R^2	0.837710	0.841851	0.840501
	MAE	20.737549	20.605859	20.747582
	MSE	783.805604	763.805997	770.328521
	RMSE	27.996528	27.637040	27.754793
	IoA	0.954937	0.954947	0.953616
RNN-ABC	R^2	**0.840512**	0.840909	0.840214
	MAE	**20.160222**	**20.253474**	20.368991
	MSE	**770.273198**	768.356943	771.713029
	RMSE	**27.753796**	27.719252	27.779723
	IoA	**0.955639**	0.954675	0.953645
RNN-FA	R^2	0.838389	0.839764	0.838719
	MSE	20.544537	20.549328	20.689894
	MSE	780.525742	773.887274	778.934971
	RMSE	27.937891	27.818829	27.909406
	IoA	0.954913	0.954277	0.952940

Table 5: Parameters selected for the best-performing models generated by the evaluated metaheuristics

Method	Learning Rate	Dropout	Epochs	Layers	Neurosn L1	Neurons L2	Neurons L3
RNN-MSCA	0.008880	0.164743	400	2	273	100	/
RNN-SCA	0.008441	0.197548	300	2	300	300	/
RNN-GA	0.008759	0.126558	517	3	162	251	100
RNN-PSO	0.000984	0.108635	484	3	199	110	119
RNN-ABC	0.010000	0.075093	594	3	186	165	246
RNN-FA	0.010000	0.200000	351	3	189	272	213

6. Conclusion

The conducted work explored the forecasting potential of RNN coupled with metaheuristic optimization for tackling sunspot prognosis. As sunspots are common precursors to solar flares that can cause geomagnetic storms and result in radio interference and damage to sensitive systems, a robust method for forecasting can help prevent infrastructure damage. To optimize the performance of RNN models, a

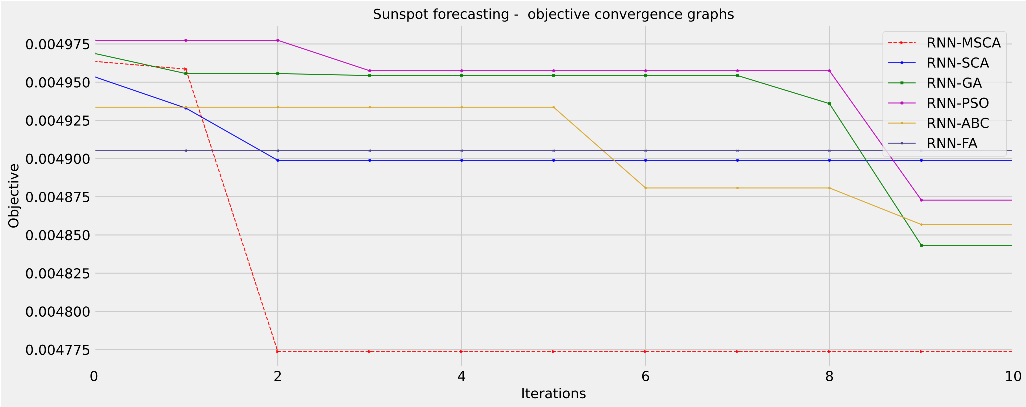

Figure 2: Objective function convergence graphs

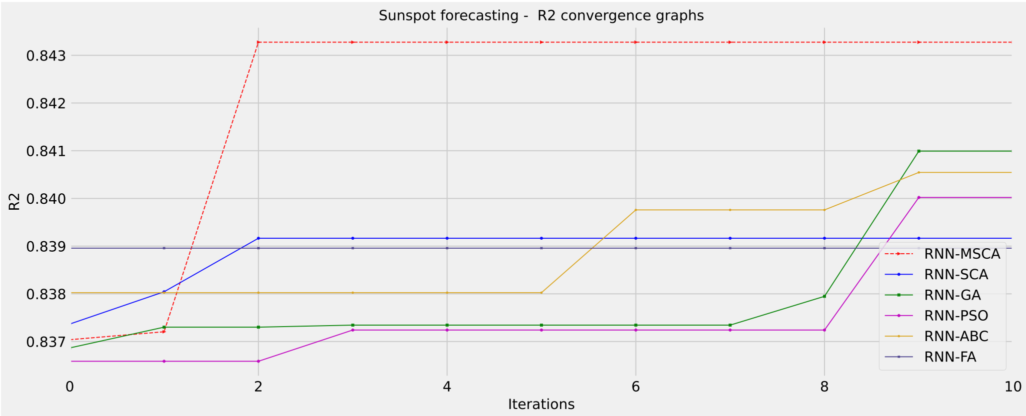

Figure 3: Indicator function convergence graphs

modified version of the well-established SCA is introduced that overcomes some of the known deficiencies of the original. Several well-known optimizer algorithms have been subjected to testing alongside the introduced modified version of the metaheuristic under identical testing continuations. Evaluated on a real-world dataset, the introduced metaheuristics demonstrated admirable performance outperforming the competition.

Future work will focus on further refining the introduced methodology and improving prediction accuracy. Additionally, the potential of the proposed approach will be explored when applied to other pressing real-world. issues.

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