A Hybrid Metaheuristic Model for Efficient Analytical Business Prediction

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***Abstract*—Accurate and efficient business analytical predictions are essential for decision making in today's competitive landscape. Involves using data analysis, statistical methods, and predictive modeling to extract insights and make decisions. Current trends focus on applying business analytics to predictions. Optimizing business analytics predictions involves increasing the accuracy and efficiency of predictive models used to forecast future trends, behavior, and outcomes in the business environment. By analyzing data and developing optimization strategies, businesses can improve their operations, reduce costs, and increase profits. The analytic business optimization method uses a hybrid PSO (Particle Swarm Optimization) and GSO (Gravitational Search Optimization) algorithm to increase the efficiency and effectiveness of the decision-making process in business. In this approach, the PSO algorithm is used to explore the search space and find the global best solution, while the GSO algorithm is used to refine the search around the global best solution. The hybrid meta-heuristic method optimizes the three components of business analytics: descriptive, predictive, and perspective. The hybrid model is designed to strike a balance between exploration and exploitation, ensuring effective search and convergence to high-quality solutions. The results show that the R2 value for each optimization parameter is close to one, indicating a more fit model. The RMSE value measures the average prediction error, with a lower error indicating that the model is performing well. MSE represents the mean of the squared difference between the predicted and optimized values. A lower error value indicates a higher level of accuracy.**

Keywords*—Efficiency; analytics business; predictions; Particle Swam Optimization (PSO); Gravitational Search Optimization (GSO)

I. Introduction

In the 4.0 Industrial Age, the availability of data is crucial for every strategic business decision [1-3]. Using analytics and algorithms, data is transformed into logical information [4]. In addition, data facilitates the consideration of visible and invisible problems in industrial operations [5-6]. Business analytics is the process of transforming data into valuable business knowledge using techniques and instruments [7-8]. Business Analytics accumulates historical business data, compiles, sorts, and then processes and analyzes the data using technology and company strategy in order to generate insights regarding company performance [9-11]. Business Analytics is a collection of techniques, technologies, and applications used to analyze company data and performance in order to make data-driven judgments regarding future investment strategies [12-13]. The three components of business analytics are descriptive analytics, the monitoring of key performance indicators to understand current business conditions, predictive analytics, the analysis of trend data to predict possible future outcomes, and prescriptive analytics, the use of past performance to generate recommendations on how to handle similar situations in the future[14-17]. For optimization purposes in predictive business analytics, metaheuristics are applied.

The purpose of metaheuristics is to efficiently explore the search space in order to find the optimal solution. Metaheuristic techniques range from simple local search procedures to complex learning processes, from simple local search procedures to complex learning processes [18]. Gravitational Search Optimization (GSO) and Particle Swam Optimization (PSO) are both metaheuristic algorithms. Based on social behavior, PSO is an evolutionary algorithm. Populate the PSO algorithm's initial state with solutions [19]. The PSO algorithm incorporates a few performance-affecting parameters that are frequently expressed as an exploratory tradeoff [20]. Exploration is the ability to evaluate different regions of the problem space in pursuit of optimal solutions. PSO is frequently used to resolve multi-objective optimization issues [21-22]. This algorithm for solving complex problems has a simple yet effective strategy for optimizing numerical functions. GSO simulates interactions between objects in a search space, where objects represent candidate solutions and gravitational forces represent solution suitability to balance exploratory and exploitative search behavior [23-24].

II. Research Methodology

A. Methodology

The data is collected from e-metrics data. In pre-processing, the data is cleaned to remove inconsistencies and is null. Perform data integration and then transform the data to be ready for analysis. Feature selection and engineering for identification of variables impact business results, and engineering new features captures more information. It is followed by processing data using the PSO algorithm to optimize model performance using the GSO Algorithm. The training and test data are separated into training and test sets. Cross-validation was carried out for model robustness and to avoid overfitting. By implementing the model in a production environment, its performance is periodically monitored to detect changes in business conditions. The research steps can be seen in Fig. 1.

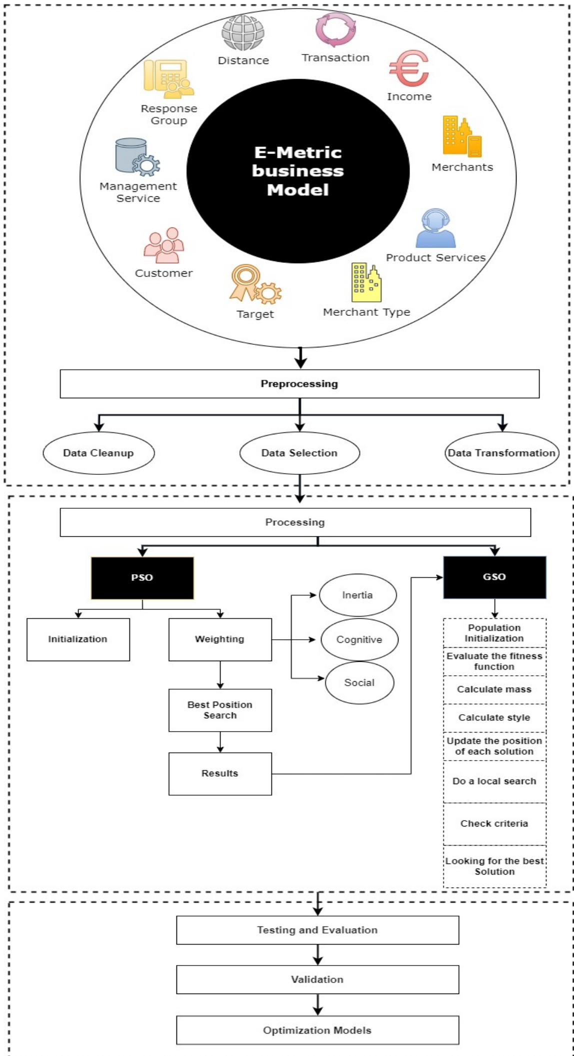

Fig. 1. Research methodology.

B. Definition of Predictive Decision Making

The process of making choices or decisions based on the analysis and interpretation of available data, patterns, and trends to forecast or predict future outcomes or events is known as predictive decision making [25]. Utilizing predictive analytics techniques and models to generate insights and estimates that can guide decision-making processes is included [26].

How can we develop accurate predictive models using machine learning techniques to forecast future business performance and identify potential optimization opportunities given the diversity of business datasets? The constructed model can account for a variety of business performance-influencing factors, such as market trends, customer behavior, and internal operations. Its purpose is to provide business stakeholders with insights and recommendations to assist them in making data-driven decisions and optimizing business operations [27]. Current trends emphasize the application of business analytics to forecasting. Fig. 2 depicts the solution to the problem, which is the optimized scope of the analytical business study.

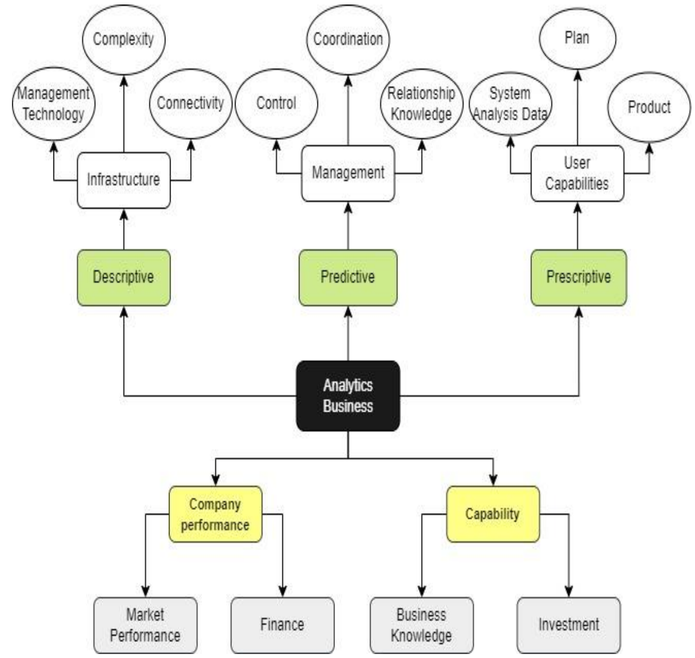

Fig. 2. Optimized analytical business review scope.

C. Classification of Data Analytics

Several advantages of big data analytics exist for obtaining valuable business insights. Here are some important benefits [28-29]:

- Enhanced Choice Making: This result is more precise and enlightened strategic planning, operational optimizations, and efficient resource allocation.
- Competitive Advantage: This information facilitates the identification of market opportunities, the development of effective marketing strategies, and the maintenance of a competitive advantage.
- Enhanced Consumer Satisfaction: This allows for targeted marketing, personalized recommendations, and superior customer experience, which ultimately increases customer satisfaction and loyalty.
- Improved Risk Management: This enables businesses to prevent fraud and mitigate risks, thereby safeguarding their assets and reputation.
- Increased Productivity: This contributes to the delivery of products and services that are more in line with consumer demands, thereby enhancing competitiveness and customer satisfaction.

The visualization is shown in Fig. 3.

D. Problem Solving Approach

In the context of optimizing business analytic predictions with the Multi-Attribute Method (MAM), Particle Swarm Optimization (PSO) can be utilized as a metaheuristic algorithm to find optimal solutions in complex search spaces. PSO is a population-based optimization technique that discovers the optimal solution by imitating the social behavior of a particle swarm.

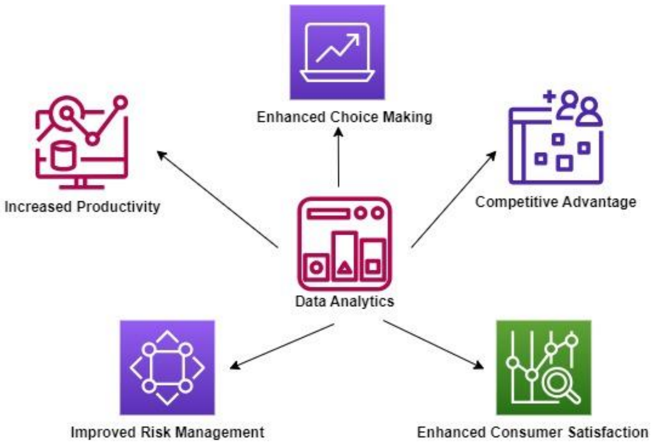

Fig. 3. Data analytics advantages for business insights.

1) Steps are done on Particle Swarm Optimization (PSO) [30]:

- Characteristics: Market conditions, customer behavior, financial indicators, and historical data are characteristics.
- Initialization of swarms: In the search space problem, the position and velocity of the particles are chosen at random.
- Fitness evaluation: Determine the fitness of each particle by calculating the value of the objective function based on the position of each particle. The fitness function indicates the efficiency or caliber of the particle solution.
- Update particle best position: Update each particle's position based on its current fitness.
- Update the highest global position: Determine the global best position by selecting the particle with the best position in the swarm.
- Update particle speed and position: Update the particle's speed and position.
- Repeat the process of fitness evaluation, updating particle best position, global best position, as well as velocity and position, until termination is reached.
- After the iteration is complete, extract the optimal solution considering the best position discovered.

To determine the optimal solution, the Particle Swarm Optimization (PSO) algorithm modifies the velocity and position of particles in the search space. Here are the formulas used by the conventional PSO algorithm [31].

PSO in training multilayer ceptrons' efficacy,

$$M_i = \{M_i^{|1|}, M_i^{|2|}\} \quad (1)$$

Position indicates the optimal fitness value for every particle,

$$S_i = \{S_i^{|1|}, S_i^{|2|}\} \quad (2)$$

seeking the optimal particle index at x,

$$A_x = \{S_x^{|1|}, S_x^{|2|}\} \quad (3)$$

Velocity update formula,

$$vl_{i(t+1)} = w * vl_{i(t)} + c_1 * rand() * (pbest_i - a_{i(t)}) + c_2 * rand() * (gbest - a_{i(t)}) \quad (4)$$

Where,

- $vl_{i(t+1)}$ at time $t+1$, is the updated velocity of particle i.
- w is the mass of inertia, which controls the influence of the previous velocity on the current velocity.
- $vl_{i(t)}$ at time t, the current velocity of particle i
- $c_1 and c_2$ acceleration coefficients that govern the effect of personal best ($pbest_i$) and global best ($gbest$) positions on the updated velocity.
- $rand()$ an arbitrary number between zero and one.
- $pbest_i$ is particle it's personal best position, indicating the highest position it has attained to date.
- $a_{i(t)}$ at time t, is the present position of particle i.
- $gbest$ is the optimal position for all particles in the swarm globally.

Position update formula,

$$a_{i(t+1)} = a_{i(t)} + v_{li(t+1)} \quad (5)$$

In this formula, $a_{i(t+1)}$ represents particle i's position updated at time $t+1$, and $vl_{i(t+1)}$ the updated velocity calculated in the previous step.

In the Particle Swam Optimization (PSO) algorithm each particle moves towards its previous personal best position (pbest) and the global best position (gbest) to achieve the optimal solution, according to Eq. (6) [32].

$$p^i_{best_x} = B_x^* | f(B_x^*) = min_{s=1,2,\dots,i}(\{(B_x^s)\}) \quad (6)$$

$$where\ x \in \{1,2,\dots,N\}$$

$$g^i_{best_x} = B_*^i | f(B_*^i) = min_{s=1,2,\dots,i}(\{(B_x^s)\})$$

x represents the particle index, i represents the current iteration number, f represents the objective function to be optimized, g represents the position vector, and N represents the total number of particles within the flock. At each x +1 iteration, the velocity D and position t of each particle i in the system are calculated. Eq. (7).

$$D_i^{x+1} = \omega D_i^x + v_1 r_1 (p^x_{best_i} - t_i^x) + v_2 r_2 (g^x_{best_i} - t_i^x)$$

$$t_i^{x+1} = t_i^x + D_i^{x+1} \quad (7)$$

D represents the velocity vector, is used to balance local exploitation and global exploration, and v_1 and r_1 are uniformly distributed random vectors in the interval [0,1]. D are the dimensions of the search space or the magnitude of the encountered problem, and v_1 and v_2 are referred to as "acceleration coefficients."

2) Gravitational search optimization (GSO): The Gravitational Search Optimization (GSO) algorithm replicates the interaction between objects in the search space, where each object represents a candidate solution and gravitational force represents the solution's suitability [33].

The formula for updating the position of the i-th solution in the population of N solutions in the GSO algorithm in Eq. (8) and (9) [34].

$$a_i = G * \left(\frac{1}{d_i^2}\right) * (\mathrm{x_{cm}} - \mathrm{x_i}) \quad (8)$$

$$b_{i(t+1)} = b_{i(t)} + c_{i(t+1)} \quad (9)$$

Where,

- a_i Solution acceleration to- i, which is determined by the force of gravity acting on the solution.
- G The gravitational constant, which controls the strength of the gravitational force.
- d_i Euclidean distance between solutions to- i and the center of mass of the solution$\mathrm{x_{cm}}$
- $b_{i(t)}$ Solution position to- i at time t
- $c_{i(t+1)}$ Updated speed from solution to- i at time $t+1$
- $b_{i(t+1)}$ The latest position of the solution to- i at time $t+1$

The approach to problem-solving that combines PSO and GSO is the PSO algorithm updates the position and velocity of the particle, then employs the GSO algorithm to update the fitness value and determine the optimal global position. The GSO algorithm can be used as an alternative to update the particle's position, while the PSO algorithm can be used to update the particle's velocity [35-37].

III. Result and Discussion

The first step is based on four segments. Segments are displayed based on the number of days that customers use to perform all activities from e-metric data. As in Table I, and the parameters used are market trends, behavior, customer needs, risk, service and product.

TABLE I. Segment

Days	Segment
<200	1
200-500	2
500-1000	3
>1000	4

To successfully implement PSO, the optimal input parameter settings must be determined. The initial value and the final value govern the search process's exploration and exploitation. An explanation is provided in Table II.

TABLE II. Definition of the PSO Process

Definition	**Information**
Selected Data	x - direction, y - direction, z = 0.5, Q wall (77, 83, 110, 125)
Number of inputs in the best intelligence	5
Swarm Size (SS) in the best of intelligence (PSO parameter)	200
Changes in Accept Ratio (AR) which are evaluated (subtractive clustering parameter)	0.5, 0.6, 0.7, 0.8, 0.9
Changes in Inertia Weight Damping Ratio (WDR) which are evaluated(PSO parameter)	0.50, 0.60, 0.70, 0.80, 0.90
P(%) percentage of data which were used in training process(while 100% of data were considered in testing process	89%
Number of data	3546
Number of iterations	600

The objective value for finding the potential of each customer is calculated using Eq. (1). The results are shown in Table III.

TABLE III. Potential Customers

Potential Customers				
	1	2	3	4
Market Trend	43.919	42.992	44.923	65.789
Behaviour	40.346	40.621	40.455	55.738
Customer Needs	54.748	53.637	43.637	56.738
Risk	53.737	57.728	53.637	63.789
Service	55.748	53.828	59.737	77.838
Product	50.763	53.728	60.738	79.748

Behavioral value is done by setting the customer's active power of each parameter based on the value of the objective function, best, worst and modifications to Eq. (2) and (3). i.e., the controlled variable related to customer status is modified to determine the best status in Eq. (6). The results are shown in Table IV.

TABLE IV. Behavioral Value

Values				
	1	2	3	4
Market Trend	0.536	-1536	0.637	0.647
Behaviour	0.787	-0.036	-1.748	0.537
Customer Needs	0.368	-0.546	0.074	0.647
Risk	-0.003	-0.002	0.004	0.003
Service	0.637	-1.738	0.647	0.663
Product	0.637	-1648	0.787	0.536

TABLE V. VELOCITY VALUE OPTIMIZATION

X[m]	Y[m]	Z[m]	Velocity [m s^-1]	Velocity u[m s^-1]	Velocity v[m s^-1]	Velocity w[m s^-1	q wall
-0.003	-0.0040	0.30006	0.8130	-0.005	0.0002	0.81320	85
-0.008	-0.0383	0.30006	0.8680	-0.005	0.0002	0.86800	85
-0.0024	-0.0034	0.30006	0.8685	-0.005	0.0003	0.86875	85
-0.028	-0.0364	0.30006	0.8143	-0.004	0.0002	0.81413	85
-0.027	-0.0378	0.30006	0.7343	-0.004	0.0002	0.73483	85
-0.002	-0.0415	0.30006	0.7331	-0.004	0.0002	0.73381	85
-0.033	-0.0033	0.30006	0.7363	-0.003	0.0002	0.73623	85
-0.031	-0.0318	0.30006	0.8154	-0.004	0.0003	0.81534	85

For optimization, vectors are used as the particle representation. The population reacts to factors based on the highest individual and group scores. The distribution of responses between individual and group values ensures response diversity. The PSO algorithm instructs multi-layered perception in which the matrix learning problem is addressed. Eq. (4) to (7) is used to calculate the new velocity of a particle based on the particle's previous velocity and the distance from its current position, using the individual's and group's greatest experience. They demonstrate cooperation between particles within a collective. Then define a new position based on the new velocity as listed in Table V.

After the PSO results are obtained, it is optimized again using GSO. According to the GSO algorithm, gravitational and inertial masses are equivalent. However, the value employed is unique. When conducting search operations, the inertial mass increases because the movement becomes slower. As shown in Fig. 4 and Fig. 5, a greater gravitational mass causes a stronger attraction, allowing for a quicker convergence.

Multi-attribute evaluations provide comparable initial statuses, and the perception training procedure starts with the most suitable initial population, as shown in Table V. Performance is shown according to the age range of customers. Because age has an important effect on the behavior of each segment attribute. Age is divided into three parts, young age range 25-35, middle age 35-55 and old age 55-65 as shown in Table VI.

The eligibility of each customer is divided by age in finding each habit, in Eq. (8) and (9). Every solution must meet quality constraints as shown in Table VII behavior at a young age, Table VIII behavior at middle age and Table IX behavior at old age. It appears that the average middle age does more activity than the young and the old.

The augmentation of the hybrid method by incorporating a memory strategy with each individual's finest fitness history. In addition, the sensitivity analysis of the parameters in this instance is optimized according to the age of the customer. Finally, comparative experiments on a set of benchmark functions were conducted to assess the performance of the hybrid model. The results are presented in Table X.

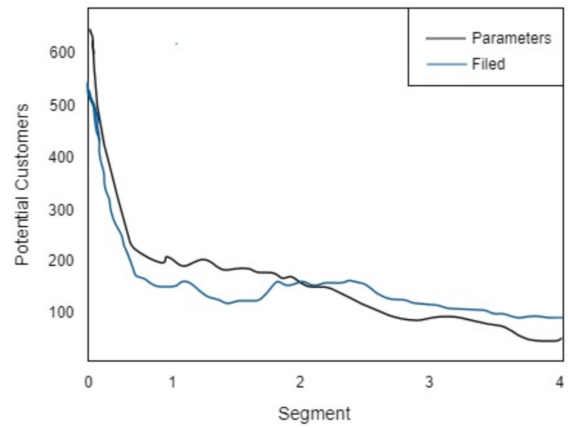

Fig. 4. Potential customer patterns.

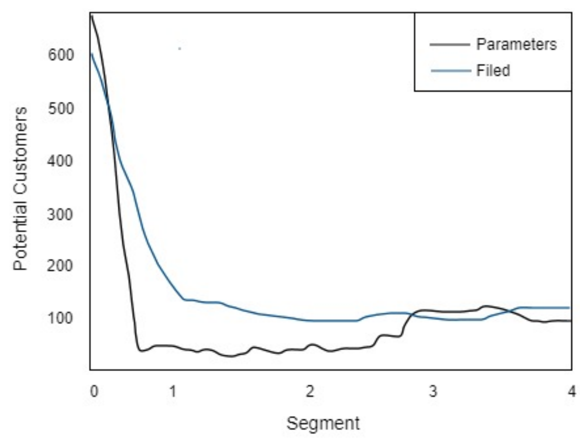

Fig. 5. Pattern of potential customers based on convergence.

TABLE VI. AGE CRITERIA

	Segments	Age Criteria
Young Age	1	25-35
Mid Age	2	35-55
Old Age	3	55-65

TABLE VII. YOUNG AGED CUSTOMERS

Young Aged Customers		
	Average Revenue	Expected Revenue
Low Income	<5,000	5,373,930
Medium Income	10,000	3,739,399
High Income	50,000	8,738,399
	Average	55,950,576

TABLE VIII. MID AGED CUSTOMERS

Mid Aged Customers		
	Average Revenue	Expected Revenue
Low Income	16,737	52,8437,301
Medium Income	26,379	8,3286,416
High Income	37,585	118,667,120
	Average	849,324,224

TABLE IX. OLD AGED CUSTOMERS

Old Aged Customers		
	Average Revenue	Expected Revenue
Low Income	8,367	264,171,291
Medium Income	16,563	522,943,599
High Income	27,389	86,475,2897
	Average	506,225,957

TABLE X. HYBRID METHOD AUGMENTATION RESULTS

Customer Segments	Count of Purchase	Sum of Segmented Customers	Conversion Rate
1	27,153	27,153	33.74
2	36,538	36,849	47.62
3	83,638	25,379	44.63
4	73,647	53,838	34.58

IV. VALIDATION

Validation using R2, RMSE and MSE where R2 indicates the proportion of variance in the dependent variable that can be attributed to the independent variable in the regression model. It ranges from 0 to 1, with greater values indicating superior models [38]. RMSE is a measure of the average prediction error of a regression model. It is the square root of the average of the squared differences between predicted and observed values [39]. MSE is similar to RMSE, but it excludes the square root. It is the average of the squared deviations between predicted and actual values [40].

The formula to calculate R2 is [41]:

$$R2 = 1 - \left(\frac{SSR}{SST}\right) \quad (10)$$

Where:

- Sum of Squares Residual (SSR) is the sum of the squared differences between anticipated and observed values.
- SST (Total Sum of Squares) is the sum of the squared differences between actual values and the mean of the dependent variable.

The formula to calculare RMSE is [42]:

$$RMSE = sqrt\left(\frac{1}{n} * \sum(y_i - y_{hat})^\wedge 2\right) \quad (11)$$

Where:

- n the quantity of observations.
- y_i represents the exact value of the dependent variable.
- y_{hat} represents the value predicted for the dependent variable.

The formula to calculate MSE is [43]:

$$MSE = \frac{1}{n} * \sum y_i - y\_hat)^\wedge 2 \quad (12)$$

Where:

- n is the number of occurrences.
- y_i represents the exact value of the dependent variable.
- y_hat represents the value predicted for the dependent variable.

Table XI displays the results, where the R2 value for each segment is close to one, indicating a superior model fit. The RMSE value assesses the average error in prediction, with a lower value indicating that the model is performing well. MSE is the mean of the squared differences between predicted and optimized values. A lower value indicates a higher level of precision.

TABLE XI. R2, RMSE, MSE VALIDATION RESULTS

Parameter		Training			Validation		
Customer Segments	Conversion Rate	R2	RMSE	MSE	R2	RMSE	MSE
1	33,74	0.87	0.17	0.08	0.87	0.20	0.11
2	47,62	0.97	0.26	0.29	0.93	0.27	0.21
3	44,63	0.85	0.36	0.28	0.91	0.41	0.35
4	34,58	0.89	0.45	0.22	0.89	0.40	0.43

Fig. 6 and Fig. 7 illustrate that the PSO Algorithm's inputs and parameters are based on social behavior, whereas the GSO is based on mass physical phenomena. In PSO, each particle modifies its position based on its own optimal position and the optimal position of the entire system. GSO, each agent's position changes dependent on the combined power of all other agents. PSO utilizes memory to update the velocity and position of particles. The GSO acceleration of the agent has an effect on the position and velocity updates. PSO particles' positions are updated without regard to the distance between solutions, whereas GSO particles' positions are updated using a force that is inversely proportional to the distance between solutions. The obtained results demonstrate that PSO improves every customer's social behavior based on their needs, current trends, risks, and services whereas GSO optimizes every condition consideration for future improvement.

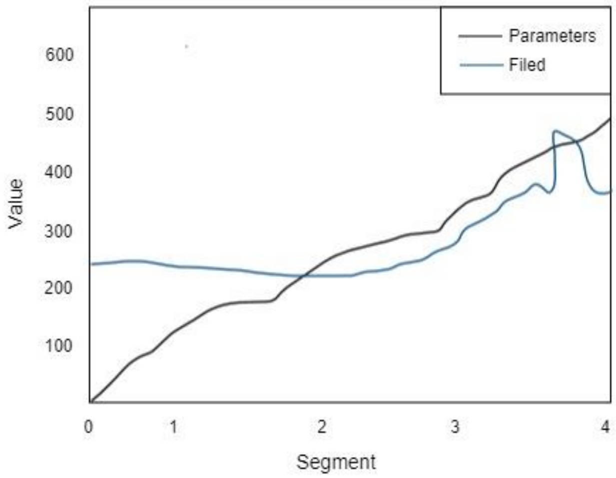

Fig. 6. Inputs and parameters of PSO and GSO algorithms are based on social behaviors.

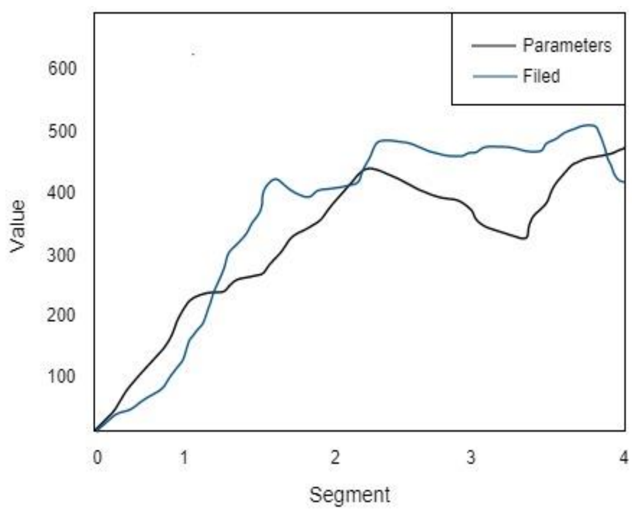

Fig. 7. The results of the optimization of the PSO and GSO algorithms based on the value social behaviors.

V. Conclusion

The conclusion of this study is that PSO and GSO are efficient meta-heuristic optimization algorithms for business analysis by augmenting a specific decision-making process or business outcome. In terms of convergence speed, precision, robustness, or scalability, the performance of PSO and GSO is analyzed. It is evidenced by the R2 validation value close to one, RMSE and MSE with lower error rates. Thus, increasing the effectiveness of these business analytics can overcome any limitations or barriers associated with the practical application of algorithms in a business environment.

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References

[1] R. Syah, M. Elveny, and M. K. M. Nasution, "Clustering Large DataSet' to Prediction Business Metrics," 2020, pp. 1117–1127. doi: 10.1007/978-3-030-63322-6_95.

[2] R. Syah, M. Elveny, M. K. M. Nasution, and G. W. Weber, "Enhanced Knowledge Acceleration Estimator Optimally with MARS to Business Metrics in Merchant Ecosystem," in 2020 4rd International Conference on Electrical, Telecommunication and Computer Engineering (ELTICOM), IEEE, Sep. 2020, pp. 1–6. doi: 10.1109/ELTICOM50775.2020.9230487.

[3] L. S. Dalenogare, G. B. Benitez, N. F. Ayala, and A. G. Frank, "The expected contribution of Industry 4.0 technologies for industrial performance," Int J Prod Econ, vol. 204, pp. 383–394, Oct. 2018, doi: 10.1016/j.ijpe.2018.08.019.

[4] H.-N. Dai, H. Wang, G. Xu, J. Wan, and M. Imran, "Big data analytics for manufacturing internet of things: opportunities, challenges and enabling technologies," Enterp Inf Syst, vol. 14, no. 9–10, pp. 1279–1303, Nov. 2020, doi: 10.1080/17517575.2019.1633689.

[5] R. H. Hamilton and W. A. Sodeman, "The questions we ask: Opportunities and challenges for using big data analytics to strategically manage human capital resources," Bus Horiz, vol. 63, no. 1, pp. 85–95, Jan. 2020, doi: 10.1016/j.bushor.2019.10.001.

[6] N. A. Ghani, S. Hamid, I. A. Targio Hashem, and E. Ahmed, "Social media big data analytics: A survey," Comput Human Behav, vol. 101, pp. 417–428, Dec. 2019, doi: 10.1016/j.chb.2018.08.039.

[7] C. Yang et al., "Big Earth data analytics: a survey," Big Earth Data, vol. 3, no. 2, pp. 83–107, Apr. 2019, doi: 10.1080/20964471.2019.1611175.

[8] M. Kraus, S. Feuerriegel, and A. Oztekin, "Deep learning in business analytics and operations research: Models, applications and managerial implications," Eur J Oper Res, vol. 281, no. 3, pp. 628–641, Mar. 2020, doi: 10.1016/j.ejor.2019.09.018.

[9] S. J. Qin and L. H. Chiang, "Advances and opportunities in machine learning for process data analytics," Comput Chem Eng, vol. 126, pp. 465–473, Jul. 2019, doi: 10.1016/j.compchemeng.2019.04.003.

[10] S. Ren, Y. Zhang, Y. Liu, T. Sakao, D. Huisingh, and C. M. V. B. Almeida, "A comprehensive review of big data analytics throughout product lifecycle to support sustainable smart manufacturing: A framework, challenges and future research directions," J Clean Prod, vol. 210, pp. 1343–1365, Feb. 2019, doi: 10.1016/j.jclepro.2018.11.025.

[11] B. Bajic, A. Rikalovic, N. Suzic, and V. Piuri, "Industry 4.0 Implementation Challenges and Opportunities: A Managerial Perspective," IEEE Syst J, vol. 15, no. 1, pp. 546–559, Mar. 2021, doi: 10.1109/JSYST.2020.3023041.

[12] M. ; N. M. K. M. ; Z. M. ; E. S. Elveny, "An advantage optimization for profiling business metrics competitive with robust nonparametric regression," J Theor Appl Inf Technol, vol. 99, pp. 114–124, 2021.

[13] M. K. M. Nasution, O. S. Sitompul, M. Elveny, and R. Syah, "Data science: A Review towards the Big Data Problems," J Phys Conf Ser, vol. 1898, no. 1, p. 012006, Jun. 2021, doi: 10.1088/1742-6596/1898/1/012006.

[14] A. Al-Khowarizmi, R. Syah, and M. Elveny, "The Model of Business Intelligence Development by Applying Cooperative Society Based Financial Technology," 2022, pp. 117–125. doi: 10.1007/978-981-16-2377-6_13.

[15] R. Syah, M. Elveny, and M. K. M. Nasution, "Performance Knowledge Acceleration Optimization with MARS to Customer Behavior in Merchant Ecosystem," in 2020 3rd International Conference on Mechanical, Electronics, Computer, and Industrial Technology (MECnIT), IEEE, Jun. 2020, pp. 178–182. doi: 10.1109/MECnIT48290.2020.9166604.

[16] Z. Huang, K. S. Savita, and J. Zhong-jie, "The Business Intelligence impact on the financial performance of start-ups," Inf Process Manag, vol. 59, no. 1, p. 102761, Jan. 2022, doi: 10.1016/j.ipm.2021.102761.

[17] M.-L. Tseng, T. P. T. Tran, H. M. Ha, T.-D. Bui, and M. K. Lim, "Sustainable industrial and operation engineering trends and challenges Toward Industry 4.0: a data driven analysis," Journal of Industrial and Production Engineering, vol. 38, no. 8, pp. 581–598, Nov. 2021, doi: 10.1080/21681015.2021.1950227.

[18] S. Mahdinia, M. Rezaie, M. Elveny, N. Ghadimi, and N. Razmjooy, "Optimization of PEMFC Model Parameters Using Meta-Heuristics," Sustainability, vol. 13, no. 22, p. 12771, Nov. 2021, doi: 10.3390/su132212771.

[19] S. S. Band et al., "Novel Ensemble Approach of Deep Learning Neural Network (DLNN) Model and Particle Swarm Optimization (PSO) Algorithm for Prediction of Gully Erosion Susceptibility," Sensors, vol. 20, no. 19, p. 5609, Sep. 2020, doi: 10.3390/s20195609.

[20] E. Bas, E. Egrioglu, and E. Kolemen, "Training simple recurrent deep artificial neural network for forecasting using particle swarm optimization," Granular Computing, vol. 7, no. 2, pp. 411–420, Apr. 2022, doi: 10.1007/s41066-021-00274-2.

[21] M. Jain, V. Saihjpal, N. Singh, and S. B. Singh, "An Overview of Variants and Advancements of PSO Algorithm," Applied Sciences, vol. 12, no. 17, p. 8392, Aug. 2022, doi: 10.3390/app12178392.

[22] T. M. Shami, A. A. El-Saleh, M. Alswaitti, Q. Al-Tashi, M. A. Summakieh, and S. Mirjalili, "Particle Swarm Optimization: A Comprehensive Survey," IEEE Access, vol. 10, pp. 10031–10061, 2022, doi: 10.1109/ACCESS.2022.3142859.

[23] M. S. Nazir et al., "Optimized economic operation of energy storage integration using improved gravitational search algorithm and dual stage optimization," J Energy Storage, vol. 50, p. 104591, Jun. 2022, doi: 10.1016/j.est.2022.104591.

[24] R. Shankar, N. Ganesh, R. Čep, R. C. Narayanan, S. Pal, and K. Kalita, "Hybridized Particle Swarm—Gravitational Search Algorithm for Process Optimization," Processes, vol. 10, no. 3, p. 616, Mar. 2022, doi: 10.3390/pr10030616.

[25] S. Arena, E. Florian, I. Zennaro, P. F. Orrù, and F. Sgarbossa, "A novel decision support system for managing predictive maintenance strategies based on machine learning approaches," Saf Sci, vol. 146, p. 105529, Feb. 2022, doi: 10.1016/j.ssci.2021.105529.

[26] M. Achouch et al., "On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges," Applied Sciences, vol. 12, no. 16, p. 8081, Aug. 2022, doi: 10.3390/app12168081.

[27] Q. Cao et al., "KSPMI: A Knowledge-based System for Predictive Maintenance in Industry 4.0," Robot Comput Integr Manuf, vol. 74, p. 102281, Apr. 2022, doi: 10.1016/j.rcim.2021.102281.

[28] H. Zhang, Z. Zang, H. Zhu, M. I. Uddin, and M. A. Amin, "Big data-assisted social media analytics for business model for business decision making system competitive analysis," Inf Process Manag, vol. 59, no. 1, p. 102762, Jan. 2022, doi: 10.1016/j.ipm.2021.102762.

[29] J. Yang, P. Xiu, L. Sun, L. Ying, and B. Muthu, "Social media data analytics for business decision making system to competitive analysis," Inf Process Manag, vol. 59, no. 1, p. 102751, Jan. 2022, doi: 10.1016/j.ipm.2021.102751.

[30] N. Y. Vanguri, S. Pazhanirajan, and T. A. Kumar, "Competitive feedback particle swarm optimization enabled deep recurrent neural network with technical indicators for forecasting stock trends," Int J Intell Robot Appl, vol. 7, no. 2, pp. 385–405, Jun. 2023, doi: 10.1007/s41315-022-00250-2.

[31] Y. Luo, J. Zhong, W.-L. Liu, and W.-N. Chen, "Automatic Business Location Selection through Particle Swarm Optimization and Neural Network," in 2023 15th International Conference on Advanced Computational Intelligence (ICACI), IEEE, May 2023, pp. 1–8. doi: 10.1109/ICACI58115.2023.10146157.

[32] X. Zhang, H. Liu, and L. Tu, "A modified particle swarm optimization for multimodal multi-objective optimization," Eng Appl Artif Intell, vol. 95, p. 103905, Oct. 2020, doi: 10.1016/j.engappai.2020.103905.

[33] S. K. , & P. D. R. Mohapatra, "A new gravitational search algorithm for global optimization," Neural Comput Appl, vol. 3, no. 29, pp. 713–733, 2018.

[34] C. Subbalakshmi, P. K. Pareek, and M. V. Narayana, "A Gravitational Search Algorithm Study on Text Summarization Using NLP," 2022, pp. 144–159. doi: 10.1007/978-3-031-21385-4_13.

[35] A. Singh and N. Singh, "Gravitational search algorithm-driven missing links prediction in social networks," Concurr Comput, vol. 34, no. 11, May 2022, doi: 10.1002/cpe.6901.

[36] N. Ayyash and F. Hejazi, "Development of hybrid optimization algorithm for structures furnished with seismic damper devices using the particle swarm optimization method and gravitational search algorithm," Earthquake Engineering and Engineering Vibration, vol. 21, no. 2, pp. 455–474, Apr. 2022, doi: 10.1007/s11803-022-2088-1.

[37] X. Hou, S. Gao, L. Qiu, Z. Li, R. Zhu, and S.-K. Lyu, "Transmission Efficiency Optimal Design of Spiral Bevel Gear Based on Hybrid PSOGSA (Particle Swarm Optimization—Gravitational Search Algorithm) Method," Applied Sciences, vol. 12, no. 19, p. 10140, Oct. 2022, doi: 10.3390/app121910140.

[38] A. Gomez-Flores, S. A. Bradford, L. Cai, M. Urík, and H. Kim, "Prediction of attachment efficiency using machine learning on a comprehensive database and its validation," Water Res, vol. 229, p. 119429, Feb. 2023, doi: 10.1016/j.watres.2022.119429.

[39] M. H. Rashidi, S. Keshavarz, P. Pazari, N. Safahieh, and A. Samimi, "Modeling the accuracy of traffic crash prediction models," IATSS Research, vol. 46, no. 3, pp. 345–352, Oct. 2022, doi: 10.1016/j.iatssr.2022.03.004.

[40] M. R. Machado and S. Karray, "Assessing credit risk of commercial customers using hybrid machine learning algorithms," Expert Syst Appl, vol. 200, p. 116889, Aug. 2022, doi: 10.1016/j.eswa.2022.116889.

[41] Z. Huang, K. S. Savita, and J. Zhong-jie, "The Business Intelligence impact on the financial performance of start-ups," Inf Process Manag, vol. 59, no. 1, p. 102761, Jan. 2022, doi: 10.1016/j.ipm.2021.102761.

[42] U. Gupta, V. Bhattacharjee, and P. S. Bishnu, "StockNet—GRU based stock index prediction," Expert Syst Appl, vol. 207, p. 117986, Nov. 2022, doi: 10.1016/j.eswa.2022.117986.

[43] Z. Fathali, Z. Kodia, and L. Ben Said, "Stock Market Prediction of NIFTY 50 Index Applying Machine Learning Techniques," Applied Artificial Intelligence, vol. 36, no. 1, Dec. 2022, doi: 10.1080/08839514.2022.2111134