Natural Obstacles and Biological Salmon Behaviors Link to Modelling Approaches of Computational Intelligence Procedures for the Standard System

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Abstract. Since classical mathematical approaches have been applied to many technical and theoretical problems, they are useful and accurate for searching solutions even they suffer from large systems and multi spaces. Recently, many algorithms have been proposed for introducing new approaches conducted to phenomena or entities in nature. Many biological behaviors and mechanisms are adopted to replace classical methods which are presented in various names as performed for the natural inspiration. In these works, the novel computational intelligence is explored in Artificial Salmon Tracking Algorithm (ASTA). ASTA is developed based on the natural obstacles and biological Salmon behaviors link to modelling approaches of computational intelligence procedures. Moreover, ASTA is applied to a standard system model considering environmental requirements for the global warming parameter. The system process is supported by suppliers to fulfill a sustainable operation while the productions are also subjected to reach clean and green targets. In these studies, ASTA is also used to optimize the system and to get an optimal portion of the balanced combination of the system results. The biological Salmon behavior presented in ASTA is also tested based on technical requirements; the results show that the solution is produced dynamically to feed the operation. The system model is balanced in various combination portions of the solution while ASTA has been demonstrated clearly to search for optimal solutions.

Keywords: Biological behaviors, salmon tracking, optimal solution, computational intelligence

1. Introduction

In general, Atlantic salmon is one of the most widely known fish species in the world, and this salmon is also one of the most abundant salmon species. Besides, this salmon has an amazing ability in tracking over rapids and low waterfalls to reach a spawning habitat. Naturally, salmon life cycles include eggs, alevins, fry, seaward migration, ocean life, spawning migration, spawning and death [1,2]. This life cycle depicts the newly hatched salmon until turning into adult salmon which lives in freshwater and migrates to the ocean. This migration is used to feed, grow, and return home from freshwater to spawn. During the migration, Salmon swims a great distance to find their home. In
detail, Salmon heading back and following rivers may cover a long distance through the vast and trackless sea [3,4]. Also, a migration can be carried out horizontally with various groups of salmon populations, where it can be done by following areas of the sea or rivers with different populations and ecological conditions. Accordingly, it has an impact and contribution to the growth of different adult salmon [5–7].

Naturally, some salmon live in the ocean for just six months, other species stay for as long as seven years. Salmon must swim upstream and jump through rapids and waterfalls. Salmon returns to their natal streams to spawn or lay eggs. Most of the salmon die along the way and do not make it back to spawn, but those that make it back lay thousands of eggs to continue the cycle of life for another generation [8,9]. Many researchers in their studies reported that they are not sure how salmon find their way. Some others also think that Salmon uses Earth's magnetic field. Other studies also explain that Salmon uses their sense of smell. Some experts speculate that salmon might use the position of the sun, or its polarized light, like a compass. Perhaps, Salmon can orient by the direction of currents or other cues in the water itself. By referring to biological characteristics, Salmon has magnetite spots on its muzzle. This shows the possibility that Salmon also migrated using the earth's magnetic field as a compass to be able to track the migration path where the position is located [4,8,10,11].

During the migration and living survival, Salmon face some predators to protect their life cycle. This obstacle makes it challenging to migrate safely. Salmon may die along the way of the migration. Moreover, Salmon has many animal predators, such as fish, ducks, and raccoons which eat salmon eggs in freshwater streams. Other fish and large insects eat salmon as alevins. As fry and smolts, salmon are hunted by large fish, minks, otters, and fish-eating birds. Larger ocean fish, seals, sea lions, orcas, and sharks hunt salmon in the oceans [10,12–15]. Once salmon begin their return migration up freshwater rivers and streams, otters, eagles, and bears hunt salmon in shallow water. Bears can catch salmon as they jump into the air over rapids and waterfalls. Moreover, fishing and farming activities also become predators of Salmon. However, some wild populations of salmon are significantly deteriorating because of fishing [12,16–18].

As in several previous works, natural behaviors and mechanisms become more attracting topics for searching suitable models and understanding the phenomena. Many behaviors of entities or species and mechanisms of processes have been selected as inspirations for developing specific computational methods based on mathematical approaches. In this paper, by considering behaviors of Salmon, its migrating mechanisms are adopted as an inspiration for Artificial Salmon Tracking Algorithm (ASTA) as an intelligent computation. This method is used to explore its processes in nature presented in an evolutionary algorithm using certain hierarchies.

2. Natural Behavior Adoption

As mentioned before, ASTA was developed by referring to the exploration mechanism during migration of the Salmon as described in this study. Salmon migration became an inspiration for the development of algorithms that mimic the hierarchy of salmon migration. In general, the life cycle of salmon in migrating can be determined by studying the entire life cycle of salmon from salmon laying and returning home from the ocean [3,5–7,18]. Besides, a series of salmon migration processes include downstream and upstream migration that face various obstacles and obstacles, both from fresh water to the ocean or the opposite as illustrated in Figure 1. Simply put, salmon moving during the time of migrating experiences some changes in their physical form according to its function, both towards the ocean after it grows large and returns to its place of origin [19]. In general, the life cycle of salmon is widely spent in rivers as a growth process by becoming a variety of predators during the migration process. Salmons that have managed to reach the sea of the burden grows into adult fish that breed and migrate back to the pond [19–22].
The characteristics of the computational speed in ASTA are built by considering the procedures and stages of migration carried out by Salmon. These steps also consider events in nature that are a process of exploration and survival against various predators. Therefore, it can reflect the real situation that exists in nature as given in Figure 2. This picture illustrates the approach model used to analogize the process of migrating salmon. The exploration step is the stage in migration which is used as a step to find the river mouth which also guides the selection of possible goals. Survival steps are used to track and find out the destination or return target used to track solutions according to the number of different branches. As given in Figure 1 and Figure 2, the computational sequence of ASTA is presented in Figure 3 as procedures to find out the solution [23,24].

**Figure 1.** Downstream and upstream mechanisms

**Figure 2.** Modeling concept of migrating behaviors
Figure 3. Procedures of ASTA

3. Model System
In this section, ASTA was applied to carry out an optimization problem using mathematical models of the IEEE-30 bus system as given in Figure 4. This problem presented economically integrated structures of various aggregates and limitations. In general, the problem covered the economic dispatch (ED) and emission dispatch (EmD). As an optimization problem related to the search for optimal solutions, this problem was directly related to the provision of high quality and reliable power to meet consumer demands at the lowest possible cost and limited by various technical and environmental conditions [25–30]. In these works, the problem was modeled and focused on the technical cost which used to decrease the running charges for the process [31,32]. In particular, a combined economic and emission dispatch (CEED) defined specifically in these works consisted of ED and EmD problems. This dispatch was also constrained by environmental criteria and technical parameters. Also, this function was used to reduce cost and emission [31,33].
By using the IEEE-30 bus as a system, the system model approach used the loss limit as much as 10%; the weighting factor is 0.5, and the emission standard is 0.85 kg/hour. Operationally, the system covers 5% of voltage limits; 95% for the power transfer; and bound to the upper and lower strength limits. Furthermore, the application of ASTA itself uses 100 of Salmon numbers, 0.25 of the Survival factors, 100 of Mouth rivers, 100 of Tracking rounds, 1 of the Migration periods, and 50 of Solution populations.

4. Results and Discussion
Considering the power loading of 283.40 MW and using the IEEE-30 bus system as a model, the simulation strived for the optimal solution of the problem that has been formulated. The total demand is one of the primary keys in the objective function of the system problem during optimizing procedures to get out the optimal solution [34–36]. In these works, the system is presented using parameters as given in Table 1 for the objective function referred to parameter coefficients. These parameters are critical to getting out the problem based on the technical requirement and conditions as discussed in many previous studies [26,31,37–41].

| Table 1. Generating unit coefficient |
|------------------------------------|
| **Gen** | **Fuel coefficients** | **Emission coefficients** |
|        | a ($/MWh^2$) | b ($/MWh$) | c | α (kg/MWh^2) | β (kg/MWh) | γ |
| G1     | 0.00375      | 2          | 0  | 0.0126       | -1.1       | 22.983 |
| G2     | 0.0175       | 1.75       | 0  | 0.02         | -0.1       | 25.313 |
| G3     | 0.0625       | 1          | 0  | 0.027        | -0.01      | 25.505 |
| G4     | 0.00835      | 3.25       | 0  | 0.0291       | -0.005     | 24.9   |
| G5     | 0.025        | 3          | 0  | 0.029        | -0.004     | 24.7   |
| G6     | 0.025        | 3          | 0  | 0.0271       | -0.0055    | 25.3   |
Table 2. Optimal condition of the power portion

| Subject | Power (MW) | Fuel Cost ($/MW) | Emission Cost ($/kg) | Emission (kg/MW) |
|---------|------------|------------------|----------------------|------------------|
| G1      | 132.55     | 330.99           | 504.31               | 231.10           |
| G2      | 41.48      | 89.41            | 119.80               | 40.51            |
| G3      | 37.8       | 80.96            | 108.86               | 37.21            |
| G4      | 25.87      | 54.25            | 75.87                | 28.83            |
| G5      | 31.63      | 67.01            | 91.33                | 32.43            |
| G6      | 37.13      | 79.43            | 106.91               | 36.64            |
| **Total** | **306.46** | **702.05**       | **1,007.09**         | **406.72**       |

As discussed in [31] that performances are major indicators to find out the problem. It can be detailed in many resulted parameters as the target of the optimization presented in the modeling function. In the optimization problem, this target was covered in the optimal solution as desired in constraints [29,35,36,40,42]. In these works, ASTA was used to search performances of the optimal solution based on the CEED as detailed in Table 2 which were presented totally in 306.46 MW of the power production. Based on the various components of the subjects, the operating cost is optimized in 1,709.13 $ meaning that the payment was used for 702.05 of the fuel costs and 1,007.09 of the emission fees. In total, the emission is discharged at 406.72 kg. Moreover, the system loss was 23.06 MW while delivering was 2803.40 MW to users. In other words, the system has 8% of the total loss. These results correspond to individual contributors who joined the system.

![Figure 5. An optimal portion of the solution](image_url)
In the optimization problem, the results can be recognized easily by numerical results, and it can also be understood using graphical performances. Both types are popular information for presenting analyzing results [42–44]. Figure 5 and Figure 6 show other results covered for the optimal operating portion and the pollutant discharge. By considering these performances, it is known that the higher contributor came from G1 as detailed in Figure 5 for the optimal power portion. This result is also related to the higher emission as presented in Figure 6.

5. Conclusion

Based on the results obtained using Artificial Salmon Tracking Algorithm, it is known that the solution was performed in different potions considered IEEE-30 bus system model. This optimal solution subjected to the technical constraints associated with power productions was linked to the optimal operating cost which is spent on the fuel consumption and the emission fee. As a further theme, the real system application is highly suggested.

Acknowledgments

Thank for the PNBP Research Grant 2018 of Universitas Negeri Malang, Malang, Jawa Timur, Indonesia.

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Figure 6. Individual discharged emission level
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