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Natural Behavior Learning for Developing an Innovation of Computational Intelligence Applied to a Technical Quadratic Problem

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Abstract— **Recently, many algorithms have been presented for new approaches based on natural inspirations as introduced in this paper is explored from the migrating Salmon mechanism. This approach is Artificial Salmon Tracking Algorithm (ASTA) which is tested on a standard system model for carrying out a dynamic economic dispatch. In these studies, ASTA is also used to optimize the system and to get an optimal portion of the balanced combination. The results show that the solution is produced dynamically to make the optimal operation for 24 hours. The system model can be balanced based on the quadratic model while ASTA has been demonstrated clearly to search for optimal solutions.**

Keywords: Economic dispatch, salmon behaviors, power commitment, technical problem, innovation development.

I. INTRODUCTION

In general, one of the meanings of a natural learning can be known as practices centered on the learning through natural life experiences, such as work experience, and social interaction [1]. Natural learning practices begin with looking at the activities and participate in living in the community [2]. The participation naturally occurs and learns opportunities in associated with routines and activities within real-life processes. The process can be figured with open-ended possibilities often an encourage participants to engage in rich play experiences [3]. In addition, natural learning resources are accessible which can be collected many things in nature where the innovation and creation are harming an inspiration.

In these works, the natural learning is emphasizing from Salmon fish species which has amazing ability while tracking over rapid flows and multiple obstacles on the migration [4]. This behavior is used to survive and stand for continuing activities and participation during living in the community. During the migration, Salmon swims a great distance to find their home which is shared in natural behavior learning for existing a community in huge migrating routes [5]. Naturally, Salmon face some predators and obstacles to keep a life cycle while migrating for surviving the life on the migrating ways [6], [7].

As in many previous works, the behavior learning presents natural mechanisms for searching suitable models and understanding the phenomena [5], [8], [9]. Many behaviors of entities or species have been selected as inspirations for developing certain approaches based on mechanisms of processes. In this paper, Salmon is considered as an inspiration based on its migrating mechanisms is associated with a natural behavior learning for Artificial Salmon Tracking Algorithm (ASTA). ASTA is performed based on the activities and participation in the community living while the survival and searching processes are collaborating in the migration.

II. LEARNING MIGRATION

In this section, ASTA is compiled using its procedures based on the exploring and surviving steps which is learned from a migration of Salmon fish corresponded to a migrating history in terms of spawning fish in fresh water, migrating to the ocean, and returning home from the ocean [10]. Moreover, the life cycle is presented for the baby salmon becomes an adult salmon which living in freshwater and migrates to the ocean [11]. During the migration for the live surviving through downstream and upstream migrations, Salmon faces some predators to keep a life cycle and also avoids obstacles to keep the migration safely [12]. In this section, the learning migration is presented in Figure 1 covered for the natural learning mechanism, natural searching inspiration, natural adopting innovation, intelligent concept construction, and computational model development.

In particular, 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 learned to become inspirations which are approached for developing certain methods [13]–[15]. In line with a natural mechanism, ASTA is referred to migrating mechanisms of Salmon as an intelligent computation [16]. In addition, this mechanism is illustrated in Figure 2 in terms of spawning fish in fresh water, migrating to the ocean, and returning home from the ocean. During these phases, the Salmon will face many predators and obstacles [17]. By considering Salmon's behavior, ASTA is constructed based on migrating steps as a computational intelligence referred to the exploring and surviving steps as illustrated in Figure 3. In ASTA, the exploring step is used to search out a mouth river for guiding the desired possibility selection. The surviving step is used to find out the returning destination to track the desired solution at all various branches [18], [19].

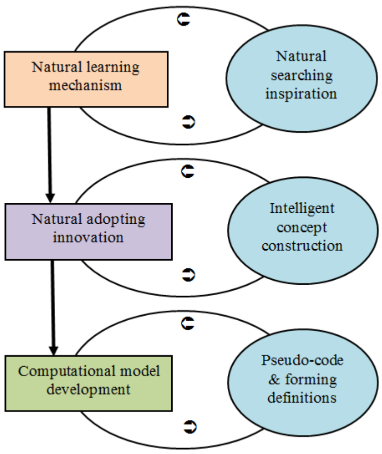

Figure 1. Natural learning inspiration

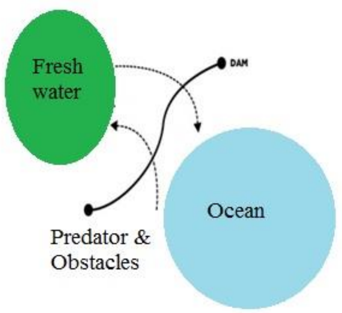

Figure 2. Salmon migrating path

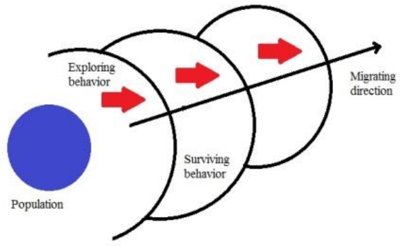

Figure 3. Salmon migrating approach model

By considering Salmon's behavior, ASTA is constructed based on migrating steps as a computational intelligence referred to the exploring and surviving steps as illustrated in Figure 3. This figure shows the salmon migrating approach model which considering the natural mechanisms of the Salmon's migrating processes [20]. In detail, downstream and upstream migrations are main keys to being designed paths of the sequences. This phase will be used to define all provided points which are pointed to the best-selected destination for opening the path to get a direction [18], [19]. Moreover, the surviving step is used to find out the returning destination to track the desired solution at all various branches. As illustrated in Figure 3, ASTA is detailed in several parameters to present the natural leaning processes in a certain sequencing inspiration in terms of salmon number, surviving factor, mouth river, tracking round, migrating period.

III. TECHNICAL LEARNING METHOD

In this section, the technical guidance is learned from the natural leaning inspiration based on the Salmon migrating path and approach model which are used to guide an implementation while ASTA is applied to a problem. By considering the exploring and surviving steps which is learned from a migration of Salmon in nature, the computational processes are given in Figure 4.

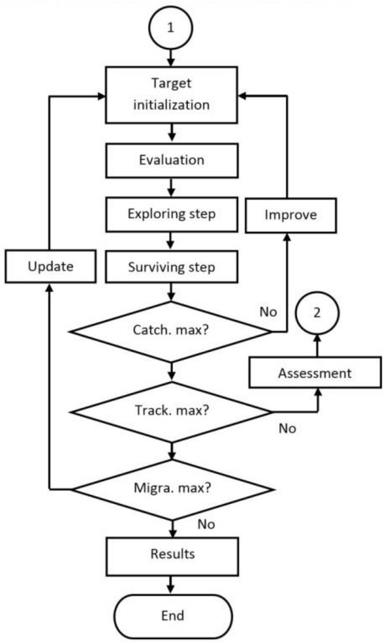

Figure 4. Computational sequences

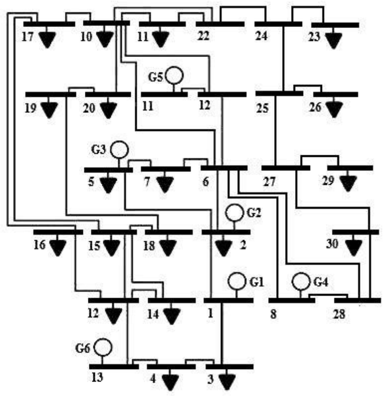

Figure 5. IEEE 30 bus system

Furthermore, Figure 4 is also used to guide the procedures and hierarchies for the optimizing problem. This figure consists of three parts as concerned in data entry with the evaluation process, exploring and surviving steps. In addition, this flowchart is also used to optimize the problem based on the sequencing algorithm to search for the best solution. In this cases, ASTA is programmed using pseudo-codes for searching the best solution using parameters in 100 of Salmon number, 0.25 of a Surviving factor, 100 of Mouth river, 100 of Tracking round, 1 of the Migrating period, and 50 of Solution population. In particular, a modeling is a more popular way than another approach to make a suitable system from the natural processes. In detail, the modeling approach is formed in clarifies assumptions, variables, and parameters [18], [19], [21], [22]. By considering the mathematical engineering, the typical mathematical modeling techniques include computer-aided design, finite element modeling, and analysis.

In these works, the model is approached using a quadratic form for the problem which is correlated to the dynamic economic dispatch (DED). This problem is constructed using an economic load dispatch (ELD) and an emission dispatch (EmD) for the 24 hours operation. By considering the period time of the operation, the DED considers load demand changes for every hour. In these studies, the IEEE-30 bus is selected as the sample system model.

IV. RESULT AND DISCUSSION

In this section, obtained results are presented in several performances as indicated parameters for the economic problem [14], [19], [23]–[25]. According to the execution of the designed programs for 24 hours, the computation's results are summarized in Table 1. This table shows results for each hour which are given in maximum and minimum points while the obtained conditions on the optimal solution are presented in Figure 6 and Figure 7.

Table 1. Maximum and minimum points of the tested system

Hour	Start ($)	Min ($)	Hour	Start ($)	Min ($)
1	525.05	523.79	13	560.08	555.72
2	513.09	511.34	14	591.46	588.77
3	518.66	517.54	15	624.40	623.00
4	527.09	523.79	16	638.26	637.01
5	538.07	536.43	17	661.89	658.38
6	571.43	568.82	18	689.14	687.51
7	584.45	582.06	19	728.55	724.98
8	590.20	588.77	20	734.82	732.62
9	624.22	623.00	21	704.52	702.36
10	637.67	637.01	22	661.07	658.38
11	624.69	623.00	23	640.93	637.01
12	589.53	588.77	24	592.80	588.77

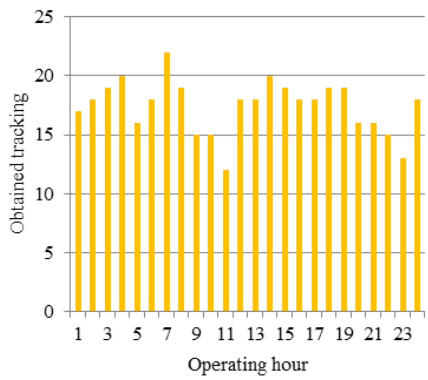

Figure 6. Obtained solution

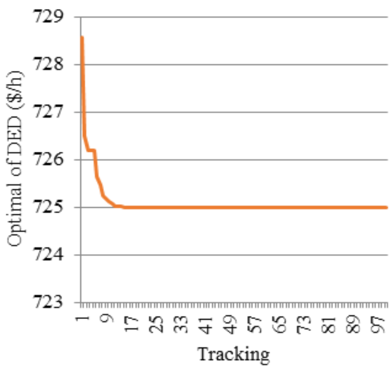

Figure 7. Computational speed

Table 2. Optimal power productions of the unit commitments

Hour	Units (MW)					
	G1	G2	G3	G4	G5	G6
1	105.26	38.86	22.53	21.79	18.71	19.13
2	103.82	38.12	22.13	21.10	18.17	18.58
3	104.54	38.49	22.33	21.45	18.44	18.85
4	105.26	38.86	22.53	21.79	18.71	19.13
5	106.69	39.61	22.93	22.49	19.25	19.68
6	110.27	41.48	23.93	24.21	20.61	21.07
7	111.76	42.25	24.35	24.84	21.14	21.61
8	112.47	42.62	24.55	25.19	21.41	21.88
9	116.05	44.49	25.56	26.92	22.78	23.27
10	117.49	45.24	25.96	27.62	23.33	23.83
11	116.05	44.49	25.55	26.92	22.78	23.27
12	112.47	42.62	24.55	25.19	21.41	21.89
13	108.84	40.73	23.53	23.52	20.07	20.51
14	112.47	42.62	24.55	25.19	21.41	21.89
15	116.05	44.49	25.56	26.92	22.78	23.27
16	117.49	45.24	25.96	27.61	23.33	23.83
17	119.63	46.37	26.57	28.66	24.15	24.66
18	122.49	47.86	27.38	30.06	25.25	25.78
19	126.07	49.74	28.40	31.80	26.63	27.17
20	126.78	50.12	28.60	32.16	26.91	27.45
21	123.92	48.62	27.79	30.75	25.80	26.33
22	119.63	46.37	26.57	28.66	24.15	24.66
23	117.49	45.24	25.96	27.62	23.33	23.83
24	112.47	42.62	24.55	25.19	21.41	21.89

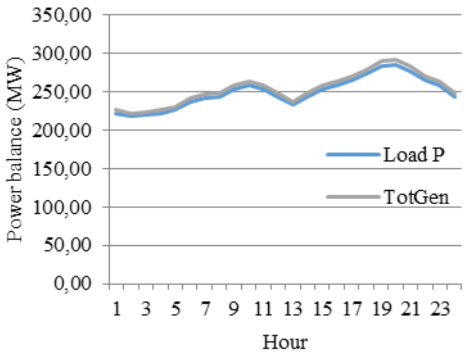

Figure 8. Power balance

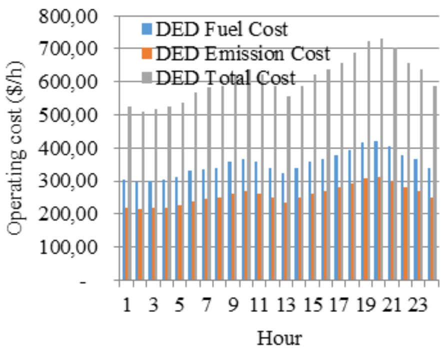

Figure 9. Operating cost

In particular, Table 2 shows the power portions of the combined unit commitment during 24-hour operations. The unit commitment is very important to show the system operation during the existing products based on the time intervals. Each combination has a contribution for supporting the optimal power balance as detailed in Figure 8. This figure informs that all possibility portions make a role in the operation base on the operating fee as presented in Figure 9. By considering all the operating time, the system provides for 5,974.66 MW of the load demand. This consumption is supplied by 6,098.08 MW from joined six generating units which means that it has 123.41 MW for the power loss. Refers to the optimal condition as depicted in Figure 8, the night load is higher than the day load with various operating cost as given in Figure 9. In details, this payment within 24-hour operations is spent for the fuel consumption around 8,438.61 $ and 6,180.22 $ for the emission compensation. Totally, the operation needs 15,618.83 $ for the 24 hou

V. CONCLUSION

This paper explores Artificial Salmon Tracking Algorithm (ASTA) development which is applied to a dynamic economic dispatch for determining the optimal operating commitment. Results obtained shows that ASTA seems to be a new approach to solve this problem. It has smooth convergence speeds with various individual portions as the unit commitment associated with the operating cost for 24 hours. From these works, future studies in real system applications are devoted to further themes.

REFERENCES

[1] P. Ofei-Manu and R. J. Didham, “Identifying the factors for sustainability learning performance,” J. Clean. Prod., vol. 198, pp. 1173–1184, Oct. 2018.

[2] W. H. Susilo, “An Impact of Behavioral Segmentation to Increase Consumer Loyalty: Empirical Study in Higher Education of Postgraduate Institutions at Jakarta,” Procedia - Soc. Behav. Sci., vol. 229, pp. 183–195, Aug. 2016.

[3] Z. A. Green and S. Batool, “Emotionalized learning experiences: Tapping into the affective domain,” Eval. Program Plann., vol. 62, pp. 35–48, Jun. 2017.

[4] N. N. Bett, S. G. Hinch, and S.-S. Yun, “Behavioural responses of Pacific salmon to chemical disturbance cues during the spawning migration,” Behav. Processes, vol. 132, pp. 76–84, Nov. 2016.

[5] J. F. Strøm, E. B. Thorstad, R. D. Hedger, and A. H. Rikardsen, “Revealing the full ocean migration of individual Atlantic salmon,” Anim. Biotelemetry, vol. 6, no. 1, p. 2, Feb. 2018.

[6] H. Ueda, “Migration and Navigation in Fish,” in Encyclopedia of Reproduction (Second Edition), M. K. Skinner, Ed. Oxford: Academic Press, 2018, pp. 84–89.

[7] M. Aldrin, P. A. Jansen, and H. Stryhn, “A partly stage structured model for the abundance of

salmon lice in salmonid farms," Epidemics, Aug. 2018.

[8] A. N. Afandi, Y. Sulistyorini, G. Fujita, N. P. Khai, and N. Tutkun, "Renewable energy inclusion on economic power optimization using thunderstorm algorithm," in 2017 4th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), 2017, pp. 1–6.

[9] A. N. Afandi, Y. Sulistyorini, H. Miyauchi, G. Fujita, X. Z. Gao, and M. El-Shimy, "The Penetration of Pollutant Productions on Dynamic Generated Power Operations Optimized Using a Novel Evolutionary Algorithm," Int. J. Adv. Sci. Eng. Inf. Technol., vol. 7, no. 5, pp. 1825–1831, Oct. 2017.

[10] S. J. Cooke, G. T. Crossin, and S. G. Hinch, "FISH MIGRATIONS | Pacific Salmon Migration: Completing the Cycle," in Encyclopedia of Fish Physiology, Elsevier, 2011, pp. 1945–1952.

[11] H. M. Hoang, T. Brown, E. Indergard, D. Leducq, and G. Alvarez, "Life cycle assessment of salmon cold chains: comparison between chilling and superchilling technologies," J. Clean. Prod., vol. 126, pp. 363–372, Jul. 2016.

[12] B. K. Wells et al., "Environmental conditions and prey-switching by a seabird predator impact juvenile salmon survival," J. Mar. Syst., vol. 174, pp. 54–63, Oct. 2017.

[13] F. S. Abu-Mouti and M. E. El-Hawary, "Optimal Distributed Generation Allocation and Sizing in Distribution Systems via Artificial Bee Colony Algorithm," IEEE Trans. Power Deliv., vol. 26, no. 4, pp. 2090–2101, Oct. 2011.

[14] A. N. Afandi, "Solving Combined Economic and Emission Dispatch Using Harvest Season Artificial Bee Colony Algorithm Considering Food Source Placements and Modified Rates," Int. J. Electr. Eng. Inform., vol. Vol. 6, p. 267, Jul. 2014.

[15] R. Ak, Y.-F. Li, V. Vitelli, and E. Zio, "Adequacy assessment of a wind-integrated system using neural network-based interval predictions of wind power generation and load," Int. J. Electr. Power Energy Syst., vol. 95, pp. 213–226, Feb. 2018.

[16] L. Jodar, J. R. Torregrosa, J. C. Cortés, and R. Criado, "Mathematical modeling and computational methods," J. Comput. Appl. Math., vol. 330, pp. 661–665, Mar. 2018.

[17] A. B. Kristoffersen, L. Qviller, K. O. Helgesen, K. W. Vollset, H. Viljugrein, and P. A. Jansen, "Quantitative risk assessment of salmon louse-induced mortality of seaward-migrating post-smolt Atlantic salmon," Epidemics, vol. 23, pp. 19–33, Jun. 2018.

[18] A. N. Afandi et al., "Evaluation Of The Power Transaction Considering The Transmission Use Of System Charges And System Constraints," PART B, p. 10, 2018.

[19] A. N. Afandi et al., "Designed Operating Approach of Economic Dispatch for Java Bali Power Grid Areas Considered Wind Energy and Pollutant Emission Optimized Using Thunderstorm Algorithm Based on Forward Cloud Charge Mechanism," Int. Rev. Electr. Eng. IREE, vol. 13, p. 59, Feb. 2018.

[20] L. E. Sundt-Hansen et al., "Modelling climate change effects on Atlantic salmon: Implications for mitigation in regulated rivers," Sci. Total Environ., vol. 631–632, pp. 1005–1017, Aug. 2018.

[21] Y. Rahmawati et al., "Developing a simulator of renewable energy as a learning media of energy conversion," IOP Conf. Ser. Earth Environ. Sci., vol. 105, p. 012079, Jan. 2018.

[22] M. Aien, A. Hajebrahimi, and M. Fotuhi-Firuzabad, "A comprehensive review on uncertainty modeling techniques in power system studies," Renew. Sustain. Energy Rev., vol. 57, pp. 1077–1089, May 2016.

[23] A. N. Afandi, I. Fadlika, and Y. Sulistyorini, "Solution of dynamic economic dispatch considered dynamic penalty factor," in 2016 3rd Conference on Power Engineering and Renewable Energy (ICPERE), 2016, pp. 241–246.

[24] A. N. Afandi and Y. Sulistyorini, "Thunderstorm Algorithm for Determining Unit Commitment in Power System Operation," J. Eng. Technol. Sci., vol. 48, no. 6, pp. 743–752, Dec. 2016.

[25] N. Tutkun, O. Can, and A. N. Afandi, "Low cost operation of an off-grid wind-PV system electrifying residential homes through combinatorial optimization by the RCGA," in 2017 5th International Conference on Electrical, Electronics and Information Engineering (ICEEIE), 2017, pp. 38–42.