# Novel self-adaptive genetic algorithm for solving AC security constrained short-term hydrothermal scheduling 

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## 1. Introduction

### 1.1. Motivation

- The optimization problem AC Security Constrained Short-term Hydrothermal Scheduling (SCSHTS) is relatively different from OPF because TPPs and HPPs are included in the power system.
- Obtaining optimal solution is not easy, because the objective function of SCSHTS has a non-convex MIP nature and AC constraints have a strong correlation.
- The classical optimization methods cannot be applied to the SCSHTS optimization problem


### 1.2. Contributions

- A compact formulation for SCSHTS problem, including all, thermal, hydro, system (AC power flow) and security constraints.
- New self-adaptive penalty which requires no parameter tuning.
- New constraint handling repair mechanism for consideration the hardest constraints, especially hydro, generator reactive, generator voltage, and bus voltage constraint, to get a significantly more realistic solution.
- A new stochastic crossover approach based on generating random number, and consequently selecting the crossover type.
- A new mutation operator, to maintain population diversity and avoid local optimum


## 2. Problem formulation

- The main objective of SCSHTS problem is to minimize the total fuel cost of thermal power plants (TPP) over the optimization period. The objective function to be minimized can be represented as:

$$
\begin{array}{ll}
\min F T=\sum_{j=1}^{J} \sum_{t=1}^{N T} F_{t, j} \cdot j & F_{t, j}=a_{t}+b_{t} \cdot P_{\mathrm{GT} t, j}+c_{t} \cdot P_{\mathrm{GT} t, j}^{2}+\mid d_{t} \sin \left(e_{t}\left(P_{\mathrm{GT} t}^{\min }-P_{\mathrm{GT} t, j}\right)\right) \\
& \forall t \in N T ; j \in J
\end{array}
$$

subject to the constraints:

- TPP constraints: generator constraint, generator voltage constraint, ramp rate constraint, available production constraint.
- HPP constraints: generator constraint, generator voltage constraint, water discharge constraint, reservoir storage, volume constraint, initial and final reservoir storage constraint, water dynamic balance constraint, available production constraint.
- Power system security constraints: AC power flow balance constraint, transmission line constraint, spinning reserve constraint, bus voltage constraint, shunt reactive power constraint.
- Control, state and dependent variables (voltage calculation by the Newton-Raphson method):

$$
\begin{gathered}
\mathbf{x}=\left\{P_{\mathrm{G}, 2}, \ldots, P_{\mathrm{G}, N T+N H}, U_{\mathrm{G}, 1}, \ldots, U_{\mathrm{G}, N T+N H}, Q_{\mathrm{Sh}, 1}, \ldots, Q_{\mathrm{Sh}, N S}\right\} \quad \mathbf{u}=\left\{U_{1}, \ldots, U_{N L}, \theta_{2}, \ldots, \theta_{N B}\right\} \\
\mathbf{y}=\left\{P_{\mathrm{G}, 1}, Q_{\mathrm{G}, 1}, \ldots, Q_{\mathrm{G}, N T+N H}, S_{\mathrm{GR}, \mathrm{~g}}, \ldots, S_{\mathrm{GR}, G}\right\}
\end{gathered}
$$

## 3. Block diagram of the proposed algorithm and test system results



|  | CCSA | MCSA | ENCSA | SAGA | Change (\%) |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $\boldsymbol{F} T_{\text {best }}(€)$ | 13722.208 | 13718.230 | 13655.538 | 12491.603 | 9.318 |
| $\boldsymbol{F T} \boldsymbol{m}_{\text {mean }}(\boldsymbol{\text { ( }}$ ) | 13759.815 | 13783.937 | 13808.732 | 12588.712 | 9.691 |
| $\boldsymbol{F} \boldsymbol{T}_{\text {worst }}(\boldsymbol{\text { ¢ }}$ ) | 13815.143 | 14066.094 | 14548.909 | 12673.007 | 14.802 |
| St. dev. (€) | 16.895 | 53.707 | 171.314 | 50.523 | 239.081 |
| CPU time (s) | 67.036 | 65.695 | 65.871 | 53.221 | 23.769 |
| Success rate (\%) | 76 | 91 | 98 | 98 | 1 |

## 4. Computational results

- After performance verification of the proposed algorithm, the same has been applied on IEEE 30 BUS SYSTEM, considering all previously defined constraints.
- The main parameters are shown as the following: gen $=300 ;$ pop $=100$; elite $=10 ; \operatorname{sim}=50$;



Optimal solution by proposed algorithm

| j | $\begin{gathered} \boldsymbol{P}_{\mathrm{GT}, 1} \\ (\mathbf{M W}) \end{gathered}$ | $\begin{aligned} & P_{\mathrm{GT}, \mathbf{2}} \\ & (\mathrm{MW}) \end{aligned}$ | $\begin{gathered} P_{\mathrm{GT}, 3} \\ (\mathrm{MW}) \end{gathered}$ | $\begin{aligned} & P_{\mathrm{GT}, 4} \\ & (\mathrm{MW}) \end{aligned}$ | $\begin{gathered} \boldsymbol{P}_{\mathrm{GH}, 1} \\ (\mathbf{M W}) \end{gathered}$ | $\begin{aligned} & \boldsymbol{P}_{\mathrm{GH}, 2} \\ & (\mathrm{MW}) \end{aligned}$ | $\begin{gathered} Q_{\text {Shn } 1} \\ \text { (MVAr) } \end{gathered}$ | $\underset{(\mathbf{M V A r})}{\boldsymbol{Q}_{\text {Sh }, 2}}$ | $\begin{gathered} S_{\mathrm{L}} \\ \text { (MVA) } \end{gathered}$ | $\underset{\left(\mathrm{m}^{3} / \mathrm{h}\right)}{Q_{1}}$ | $\underset{\left(\mathrm{m}^{3} / \mathrm{h}\right)}{Q_{2}}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 94.80 | 25.55 | 15.00 | 12.04 | 10.00 | 12.00 | 4.83 | 0.01 | 13.76 | 143.33 | 235.91 |
| 2 | 115.88 | 35.86 | 0.00 | 16.81 | 10.97 | 22.07 | 13.96 | 0.70 | 22.07 | 151.84 | 413.85 |
| 3 | 129.35 | 48.38 | 15.00 | 23.67 | 19.17 | 0.00 | 8.84 | 3.00 | 28.23 | 224.40 | 0.00 |
| 4 | 130.07 | 57.91 | 25.50 | 26.79 | 0.00 | 34.47 | 18.55 | 0.79 | 31.42 | 0.00 | 635.70 |
| 5 | 130.70 | 51.01 | 30.05 | 26.64 | 18.81 | 33.71 | 18.10 | 3.87 | 30.89 | 221.21 | 622.05 |
| 6 | 126.98 | 47.42 | 31.39 | 24.35 | 18.15 | 30.62 | 13.06 | 2.47 | 28.41 | 215.33 | 566.52 |
| 7 | 128.96 | 52.12 | 25.40 | 26.68 | 19.57 | 0.00 | 5.36 | 2.22 | 29.52 | 228.01 | 0.00 |
| 8 | 116.29 | 38.44 | 15.00 | 17.29 | 10.34 | 21.10 | 4.13 | 1.60 | 21.75 | 146.31 | 396.61 |
| 9 | 119.90 | 42.72 | 0.00 | 17.92 | 17.20 | 0.00 | 13.53 | 3.44 | 24.19 | 206.94 | 0.00 |
| 10 | 99.64 | 27.58 | 15.00 | 12.28 | 10.00 | 0.00 | 18.78 | 0.57 | 15.47 | 143.33 | 0.00 |
| 11 | 91.40 | 20.54 | 16.03 | 11.84 | 10.00 | 0.00 | 12.24 | 2.77 | 12.53 | 143.33 | 0.00 |
| 12 | 93.11 | 24.64 | 15.53 | 12.13 | 0.00 | 17.87 | 1.72 | 3.67 | 13.28 | 0.00 | 339.33 |
| 13 | 104.12 | 29.33 | 17.14 | 12.82 | 10.45 | 0.00 | 7.01 | 3.56 | 16.51 | 147.25 | 0.00 |
| 14 | 103.03 | 33.26 | 19.93 | 13.26 | 0.00 | 19.75 | 9.74 | 0.50 | 17.03 | 0.00 | 372.60 |
| 15 | 113.20 | 34.66 | 21.13 | 13.97 | 10.00 | 20.00 | 16.99 | 2.99 | 20.13 | 143.33 | 377.11 |
| 16 | 119.22 | 39.24 | 25.25 | 16.56 | 13.03 | 24.40 | 13.24 | 0.90 | 22.96 | 169.99 | 455.30 |
| 17 | 138.03 | 41.80 | 27.19 | 18.68 | 15.33 | 12.00 | 14.49 | 0.39 | 28.93 | 190.38 | 235.91 |
| 18 | 120.11 | 43.61 | 22.13 | 21.41 | 14.15 | 25.77 | 3.05 | 1.23 | 24.95 | 179.88 | 479.70 |
| 19 | 118.83 | 50.20 | 15.00 | 22.32 | 12.22 | 23.71 | 9.58 | 4.13 | 25.32 | 162.88 | 442.99 |
| 20 | 145.52 | 59.91 | 0.00 | 28.04 | 0.00 | 0.00 | 13.70 | 3.23 | 35.74 | 0.00 | 0.00 |
| 21 | 110.35 | 38.50 | 15.00 | 16.61 | 10.00 | 18.57 | 8.23 | 0.97 | 20.13 | 143.33 | 351.74 |
| 22 | 102.69 | 32.82 | 16.79 | 13.96 | 0.00 | 19.95 | 5.23 | 2.38 | 16.91 | 0.00 | 376.28 |
| 23 | 93.54 | 20.00 | 15.00 | 10.00 | 10.00 | 15.61 | 4.86 | 3.43 | 12.82 | 143.33 | 299.48 |
| 24 | 86.66 | 20.00 | 15.00 | 0.00 | 0.00 | 12.00 | 4.92 | 0.52 | 10.86 | 0.00 | 235.91 |

## Optimal bus voltages by proposed algorithm

| $i / j$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 88 |
| 2 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 88 |
| 3 | 0.979 | 0.979 | 0.971 | 0.968 | 0.968 | 0.968 | 0.967 | 0.973 | 0.978 | 0.981 | 0.981 | 0.980 | 0.978 | 0.979 | 0.976 | 0.973 | 0.968 | 0.969 | 0.973 | 0.967 | 0.974 | 0.979 | 0.980 | 0.981 |
| 4 | 0.976 | 0.976 | 0.966 | 0.963 | 0.963 | 0.963 | 0.961 | 0.969 | 0.975 | 0.978 | 0.978 | 0.977 | 0.975 | 0.976 | 0.972 | 0.969 | 0.963 | 0.964 | 0.968 | 0.961 | 0.970 | 0.976 | 0.977 | 0.979 |
| 5 | 0.988 | 0.988 | 0.978 | 0.968 | 0.968 | 0.968 | 0.978 | 0.978 | 0.988 | 0.988 | 0.98 | 0.988 | 0.988 | 0.988 | 0.988 | 0.978 | 0.978 | 0.978 | 0.978 | 0.968 | 0.988 | 0.988 | 0.988 | 0.988 |
| 6 | 0.981 | 0.981 | 0.971 | 0.964 | 0.965 | 0.964 | 0.964 | 0.972 | 0.98 | 0.984 | 0.984 | 0.981 | 0.981 | 0.981 | 0.976 | 0.972 | 0.966 | 0.965 | 0.972 | 0.964 | 0.974 | 0.981 | 0.982 | 0.983 |
| 7 | 0.980 | 0.979 | 0.968 | 0.958 | 0.958 | 0.958 | 0.963 | 0.969 | 0.97 | 0.981 | 0.982 | 0.980 | 0.97 | 0.979 | 0.975 | 0.968 | 0.963 | 0.964 | 0.968 | 0.959 | 0.974 | 0.979 | 0.980 | 0.982 |
| 8 | 0.988 | 0.988 | 0.978 | 0.968 | 0.968 | 0.968 | 0.9 | 0.978 | 0.9 | 0.988 | 0.9 | 0.988 | 0.988 | 0.988 | 0.97 | 0.978 | 0.968 | 0.968 | 0.978 | 0.968 | 0.978 | 0.988 | 0.988 | 0.988 |
| 9 | 0.99 | 0.99 | 0.98 | 0.980 | 0.980 | 0.978 | 0.97 | 0.982 | 0.99 | 1. | 1.00 | 0.992 | 0.99 | 0.992 | 0.992 | 0.98 | 0.981 | 0.976 | 0.984 | 0.983 | 0.986 | 0.99 | 0.994 | 96 |
| 10 | 0.989 | 0.993 | 0.979 | 0.973 | 0.974 | 0.970 | 0.968 | 0.974 | 0.997 | 1.010 | 1.005 | 0.987 | 0.994 | 0.989 | 0.993 | 0.980 | 0.976 | 0.964 | 0.978 | 0.979 | 0.980 | 0.986 | 0.992 | 0.996 |
| 11 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.998 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | . 988 |
| 12 | 1.003 | 1.004 | 0.988 | 0.988 | 0.987 | 0.986 | 0.983 | 0.991 | 1.002 | 1.013 | 1.012 | 1.005 | 1.003 | 1.003 | 1.002 | 0.992 | 0.987 | 0.986 | 0.992 | 0.988 | 0.993 | 1.003 | 1.005 | 1.012 |
| 13 | 0.998 | 0.998 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.998 | 1.008 | 1.008 | 0.998 | 0.998 | 0.998 | 0.998 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.988 | 0.998 | 0.998 | 1.008 |
| 14 | 0.993 | 0.993 | 0.976 | 0.973 | 0.972 | 0.971 | 0.968 | 0.979 | 0.992 | 1.0 | 1.0 | 0.995 | 0.994 | 0.993 | 0.991 | 0.979 | 0.973 | 0.971 | 0.979 | 0.976 | 0.982 | 0.993 | 0.996 | 1.004 |
| 15 | 0.989 | 0.989 | 0.973 | 0.967 | 0.966 | 0.965 | 0. | 0.974 | 0.990 | 1.002 | 1. | 0.991 | 0.991 | 0.989 | 0.987 | 0.974 | 0.969 | 0.966 | 0.974 | 0.972 | 0.978 | 0.988 | 0.993 | 1.001 |
| 16 | 0.992 | 0.994 | 0.978 | 0.974 | 0.974 | 0.972 | 0.970 | 0.978 | 0.995 | 1.007 | 1.005 | 0.993 | 0.994 | 0.992 | 0.992 | 0.980 | 0.976 | 0.970 | 0.979 | 0.978 | 0.982 | 0.991 | 0.995 | 1.002 |
| 17 | 0.986 | 0.989 | 0.974 | 0.968 | 0.968 | 0.965 | 0.964 | 0.971 | 0.993 | 1.006 | 1.002 | 0.986 | 0.991 | 0.986 | 0.989 | 0.975 | 0.971 | 0.961 | 0.973 | 0.974 | 0.977 | 0.984 | 0.990 | 0.995 |
| 18 | 0.982 | 0.982 | 0.965 | 0.957 | 0.956 | 0.954 | 0.954 | 0.96 | 0.98 | 0.998 | 0.99 | 0.983 | 0.984 | 0.980 | 0.980 | 0.96 | 0.960 | 0.95 | 0.965 | 0.964 | 0.969 | 0.979 | 0.985 | 0.993 |
| 19 | 0.97 | 0.980 | 0.962 | 0.954 | 0.953 | 0.951 | 0.95 | 0.96 | 0.98 | 0.99 | 0.9 | 0.98 | 0.98 | 0.97 | 0.9 | 0.9 | 0.9 | 0.95 | 0. | 0.962 | 0.967 | 0.97 | 0.983 | 0.990 |
| 20 | 0.98 | 0.982 | 0.96 | 0.95 | 0.958 | 0.955 | 0.955 | 0.96 | 0.98 | 1.0 | 0.99 | 0.98 | 0.98 | 0.98 | 0.98 | 0.96 | 0.9 | 0.9 | 0. | 0.96 | 0.970 | 0.97 | 0.985 | 0.991 |
| 21 | 0.98 | 0.98 | 0.9 | 0.9 | 0.962 | 0.958 | 0.95 | 0. | 0.98 | 1.0 | 0.9 | 0.982 | 0.987 | 0.9 | 0.9 | 0. | 0. | 0.953 | 0. | 0.969 | 0.971 | 0.97 | 0.986 | 0.991 |
| 22 | 0.982 | 0.98 | 0.9 | 0.9 | 0. | 0.95 | 0.9 | 0. | 0.9 | 1.003 | 0. | 0.982 | 0. | 0. | 0. | 0. | 0. | 0.954 | 0. | 0. | 0.972 | 0.98 | 0.987 | 0.991 |
| 23 | 0.982 | 0.981 | 0.9 | 0.955 | 0.95 | 0.954 | 0.95 | 0.965 | 0.9 | 0.997 | 0.9 | 0.985 | 0. | 0. | 0. | 0.965 | 0.95 | 0.95 | 0.966 | 0.965 | 0.969 | 0.981 | 0.987 | 0.994 |
| 24 | 0.977 | 0.977 | 0.962 | 0.948 | 0.952 | 0.948 | 0.949 | 0.959 | 0.984 | 0.994 | 0.996 | 0.982 | 0.985 | 0.975 | 0.977 | 0.960 | 0.953 | 0.946 | 0.963 | 0.962 | 0.964 | 0.977 | 0.985 | 0.989 |
| 25 | 0.984 | 0.982 | 0.968 | 0.953 | 0.954 | 0.952 | 0.956 | 0.967 | 0.988 | 0.997 | 0.998 | 0.988 | 0.990 | 0.982 | 0.979 | 0.966 | 0.958 | 0.953 | 0.967 | 0.966 | 0.971 | 0.983 | 0.990 | 0.994 |
| 26 | 0.973 | 0.969 | 0.953 | 0.935 | 0.935 | 0.934 | 0.939 | 0.953 | 0.975 | 0.987 | 0.989 | 0.978 | 0.979 | 0.970 | 0.966 | 0.950 | 0.941 | 0.937 | 0.952 | 0.951 | 0.958 | 0.971 | 0.979 | 0.986 |
| 27 | 0.994 | 0.991 | 0.979 | 0.965 | 0.964 | 0.964 | 0.968 | 0.978 | 0.996 | 1.003 | 1.005 | 0.997 | 0.998 | 0.992 | 0.987 | 0.977 | 0.969 | 0.966 | 0.978 | 0.975 | 0.981 | 0.993 | 0.998 | 1.002 |
| 28 | 0.983 | 0.982 | 0.971 | 0.962 | 0.963 | 0.963 | 0.963 | 0.972 | 0.982 | 0.985 | 0.985 | 0.983 | 0.983 | 0.982 | 0.976 | 0.972 | 0.964 | 0.964 | 0.972 | 0.964 | 0.974 | 0.982 | 0.984 | 0.985 |
| 29 | 0.982 | 0.978 | 0.962 | 0.945 | 0.943 | 0.943 | 0.950 | 0.962 | 0.982 | 0.992 | 0.994 | 0.986 | 0.986 | 0.979 | 0.972 | 0.960 | 0.951 | 0.948 | 0.961 | 0.959 | 0.967 | 0.980 | 0.986 | 0.992 |
| 30 | 0.975 | 0.969 | 0.953 | 0.933 | 0.931 | 0.931 | 0.939 | 0.953 | 0.975 | 0.986 | 0.989 | 0.979 | 0.979 | 0.971 | 0.964 | 0.950 | 0.940 | 0.937 | 0.951 | 0.949 | 0.958 | 0.972 | 0.980 | 0.987 |

- From Table 2, the effectiveness of the proposed SAGA can be seen. SAGA gives the lowest total fuel costs, i.e., $12491.603 €$, compared to the ENCSA whose total fuel costs are $13655.538 €$. In other words, the total fuel costs obtained with SAGA are by $1163.935 €$ lower compared to ENCSA, which in relative terms implies an improvement of $9.318 \%$.
- SAGA shows its superiority in dealing with constraints, whereas compared to ENCSA it maintains the same successful rate of $98 \%$, but compared to other CCSA and MCSA, it is higher by $22 \%$ and $7 \%$, respectively. On the other hand, $F T_{\text {mean }}$ obtained by SAGA from the successful simulations has the lowest value compared to other metaheuristic methods.
- This is due to the newly proposed constraints handling approach, the newly proposed stochastic approach for the crossover operator, as well as the adaptive crossover and mutation strategies, which increase the crossover and mutation probability, only on those chromosomes whose fitness function is significantly different from the mean fitness function of the entire population.


## 5. Conclusion

- SCSHTS is an important task in the operation and planning of modern power systems. In this paper, a novel GA-based algorithm has been proposed and successfully applied to solve AC constrained short-term hydrothermal scheduling problem. To verify the efficiency of the proposed algorithm, it is first applied to the benchmark version of the IEEE 30 BUS test system, and then to the classic IEEE 30 BUS test system, considering all predefined constraints.
- The results obtained by the proposed method have been compared with other evolutionary algorithms like CCSA, MCSA, and ENCSA. It is found that the proposed SAGA can produce better results in terms of cost and computation time. The results show that the proposed GA-based algorithm is indeed capable of obtaining good quality solution efficiently in case of shortterm hydrothermal scheduling problems, considering AC power flow model to obtain realistic solution.

