

Sustainable Energy Systems
School of Engineering and Computer Science
Faculty of Engineering
Victoria University of Wellington

Optimal Sizing of an Islanded Micro-Grid Using Meta-Heuristic Optimization Algorithms Considering Demand-Side Management



Soheil Mohseni

Supervisors: Professor Alan C. Brent and Dr. Daniel Burmester

- Introduction and Significance
- Research Objectives
- Methodology
- Simulation Results
- Key Findings

Introduction and Significance

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- The necessity of micro-grid sizing
- Considering DSM strategies: Peak load reduction
- The need for advanced heuristics to optimize the problem
- Alleviating the computational burden: Pave the way for incorporating other features (e.g. uncertainty analysis) into the problem

Research Objectives

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Developing a method for optimal sizing of the components of micro-grids that:

- Incorporates a DRP
- Reduces the computational complexity
- Improves the solution accuracy compared with the state-of-the art

Micro-Grid Test System

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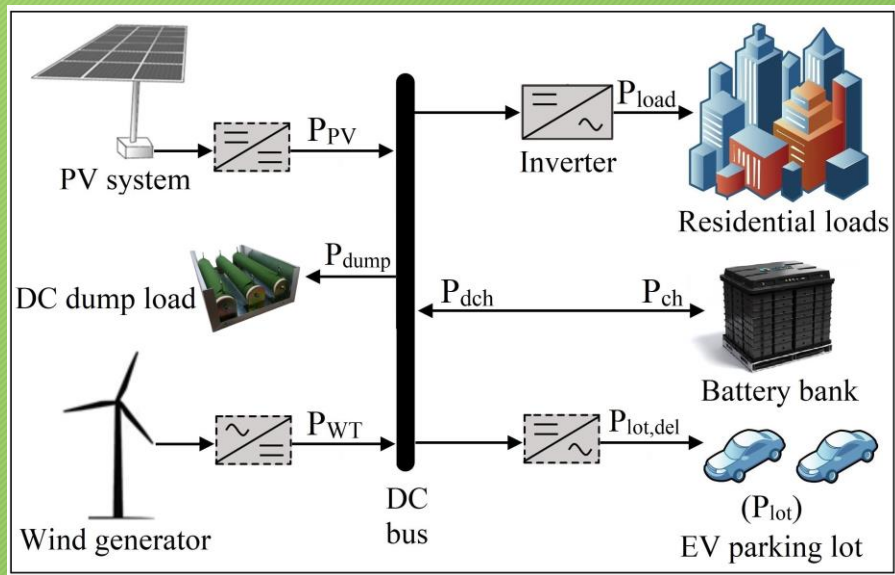


Fig. 1. Micro-grid test system

Case study: Hengam Island, Persian Gulf, Iran

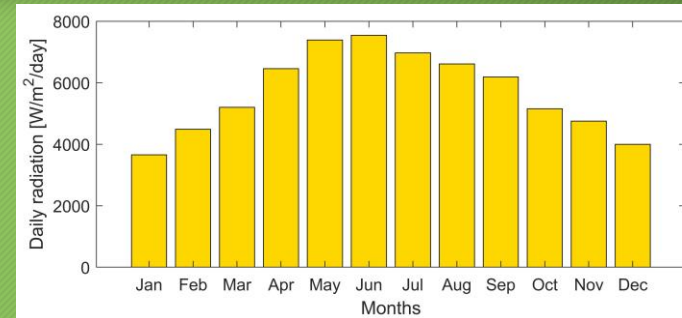


Fig. 2. Monthly average daily solar irradiance at the considered site

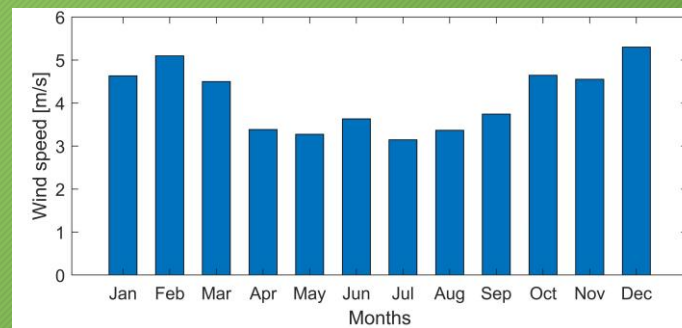


Fig. 3. Monthly average wind speed at the considered site

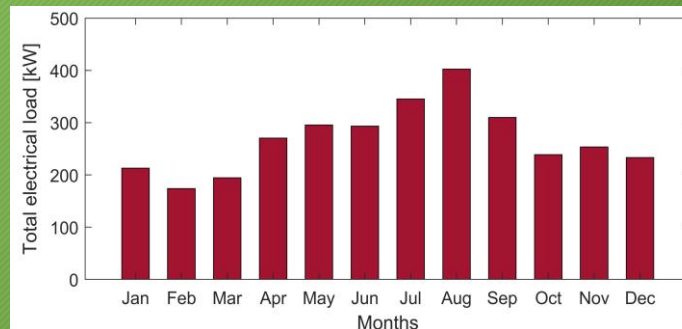


Fig. 4. Monthly average total load on the micro-grid

The proposed method consists mainly of five parts:

- A model reduction technique
- A DLC-DR program
- A reliability assessment plan
- An objective function
- A meta-heuristic optimization algorithm, i.e. the MFOA [1]

Data compression-based model reduction technique:

Reduces the annual profiles for weather and load forecasts to monthly-averaged daily profiles, motivated by [2].

DLC-DR program:

Shifts an appropriate percentage of the electrical loads on the micro-grid system from peak to off-peak consumption hours.

Reliability assessment plan:

$$ELF_{load} = \frac{1}{n} \sum_{t=1}^n \frac{Q_{load}(t)}{P_{load}(t)}, \quad ELF_{lot} = \frac{1}{n} \sum_{t=1}^n \frac{Q_{lot}(t)}{P_{lot}(t)}$$

* $ELF_{load} < 0.01$, $ELF_{lot} < 0.02$

Objective function:

Net Present Cost [3]:

$$NPC_{total} = NPC_{PV} + NPC_{WT} + NPC_{bat} + NPC_{inv} + NPC_{EVSE} + \overbrace{pen_{load} + pen_{lot}}^{\text{Rel. cons.}} + \overbrace{pen_{bat}}^{\text{Oper. cons.}}$$

$$NPC = \underbrace{N}_{\text{capacity}} \times \left(CC + RC \times K + O\&M \times \frac{1}{CRF(ir, R)} - SV \right) \quad CRF(ir, R) = \frac{ir(1 + ir)^R}{(1 + ir)^R - 1}$$

$$K = \sum_{p=1}^Y \frac{1}{(1 + ir)^{L \times p}}$$

ir=6%
R=25 years

$$Y = \begin{cases} \left\lceil \frac{R}{L} \right\rceil - 1 & \text{if } R \text{ is dividable to } L \\ \left\lceil \frac{R}{L} \right\rceil & \text{if } R \text{ is not dividable to } L \end{cases}$$

lifetime

Optimization algorithm: the MFOA, i.e. a state of the art swarm-based meta-heuristic algorithm

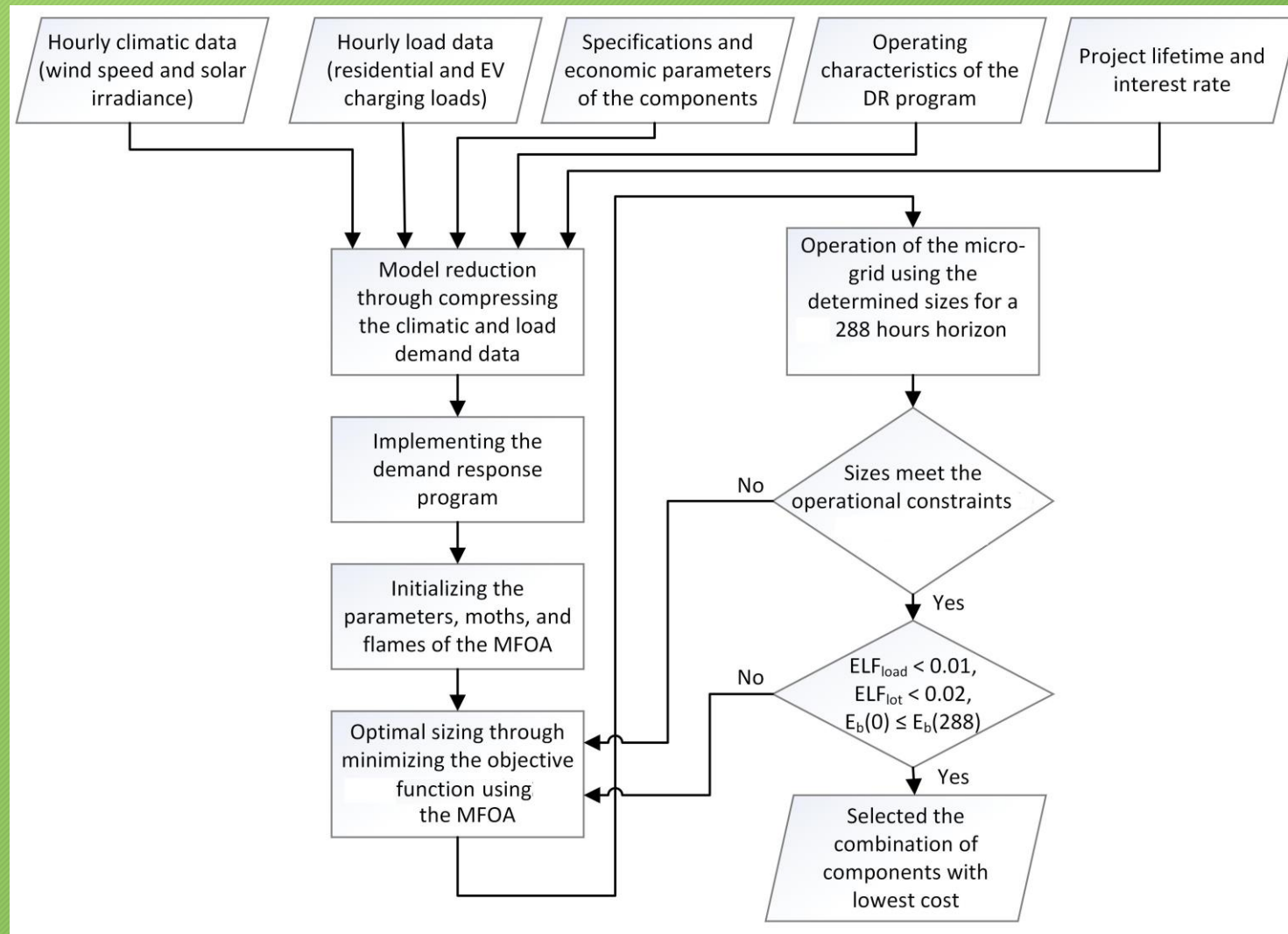


Fig. 5. A panorama of the optimization process for micro-grid sizing

Simulation Results

Table 1. Verification of the model reduction technique

Case	PV panels	WTs	Battery packs	Inverter [kW]	EVSE	Total NPC [\$]	CPU utilization time [h]
With model reduction	687	45	58	339	6	4,506,020	13
Without model reduction	669	44	55	334	6	4,424,830	384



A remarkable saving in CPU time with an only 2% increment in total NPC

Table 2. Verification of the MFOA

Optimization algorithm	PV panels	WTs	Battery packs	Inverter [kW]	EVSE	Total NPC [\$]
MFOA	687	45	58	339	6	4,506,020
Hybrid GA-PSO	688	45	58	346	7	4,518,573
GA	688	46	59	341	7	4,532,088
PSO	687	45	82	335	7	4,552,670

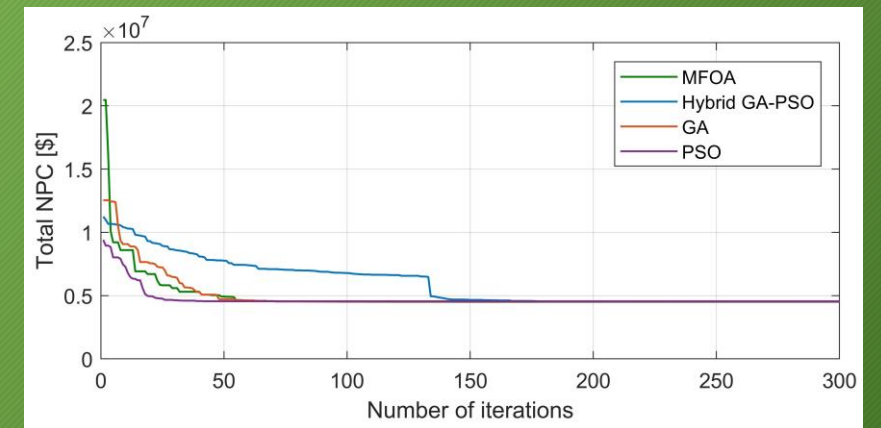


Fig. 6. Total NPC of the micro-grid in terms of iterations

Verification of the load shifting property of the method:

Time window of the load shifting = 4 h

Percentage of deferrable loads in the total load demand = 20%

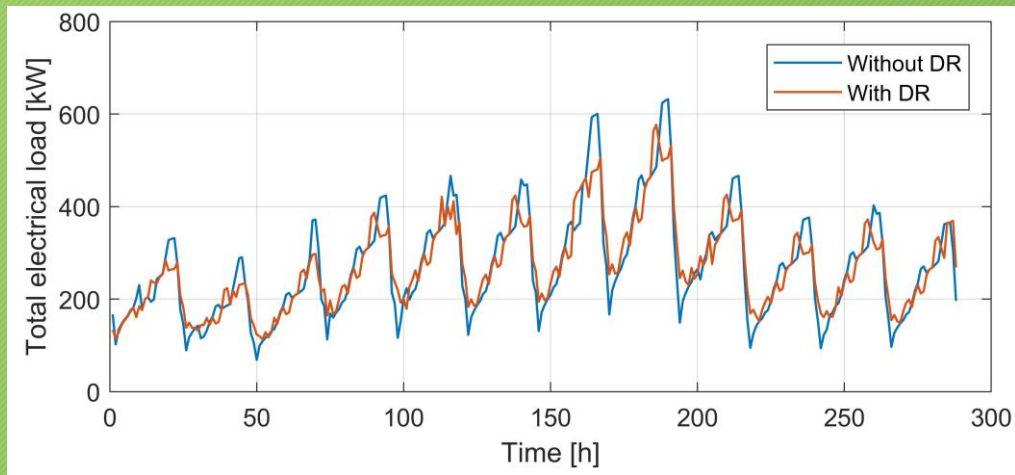


Fig. 7. Impact of employing the DR program on the load curve

Table 3. The results obtained with and without DR deployment

Case	PV panels	WTs	Battery packs	Inverter [kW]	EVSE	Total NPC [\$]
With DR	687	38	76	319	5	4,182,817
Without DR	687	45	58	339	6	4,506,020

7% reduction in total NPC

Sensitivity analysis

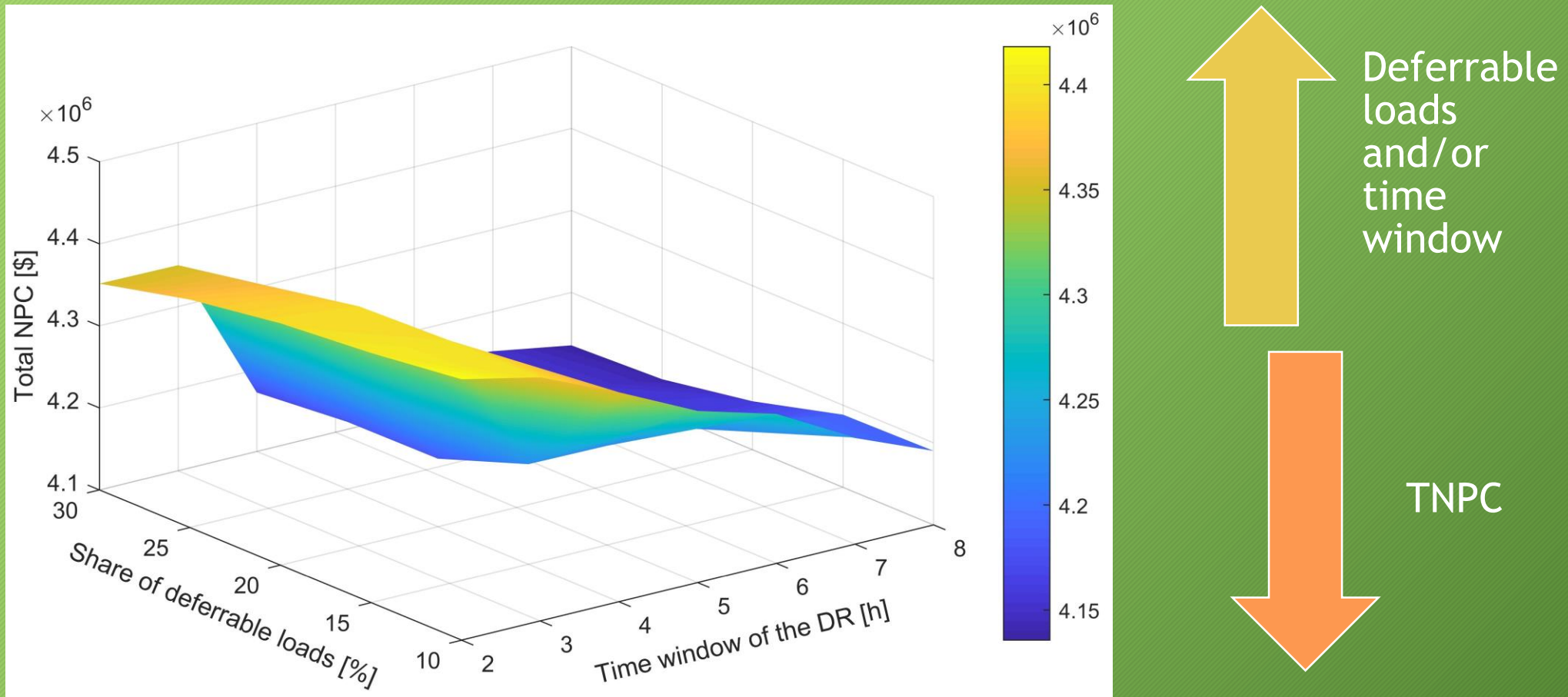


Fig. 8. Sensitivity of the total NPC to the operating characteristics of the DRP

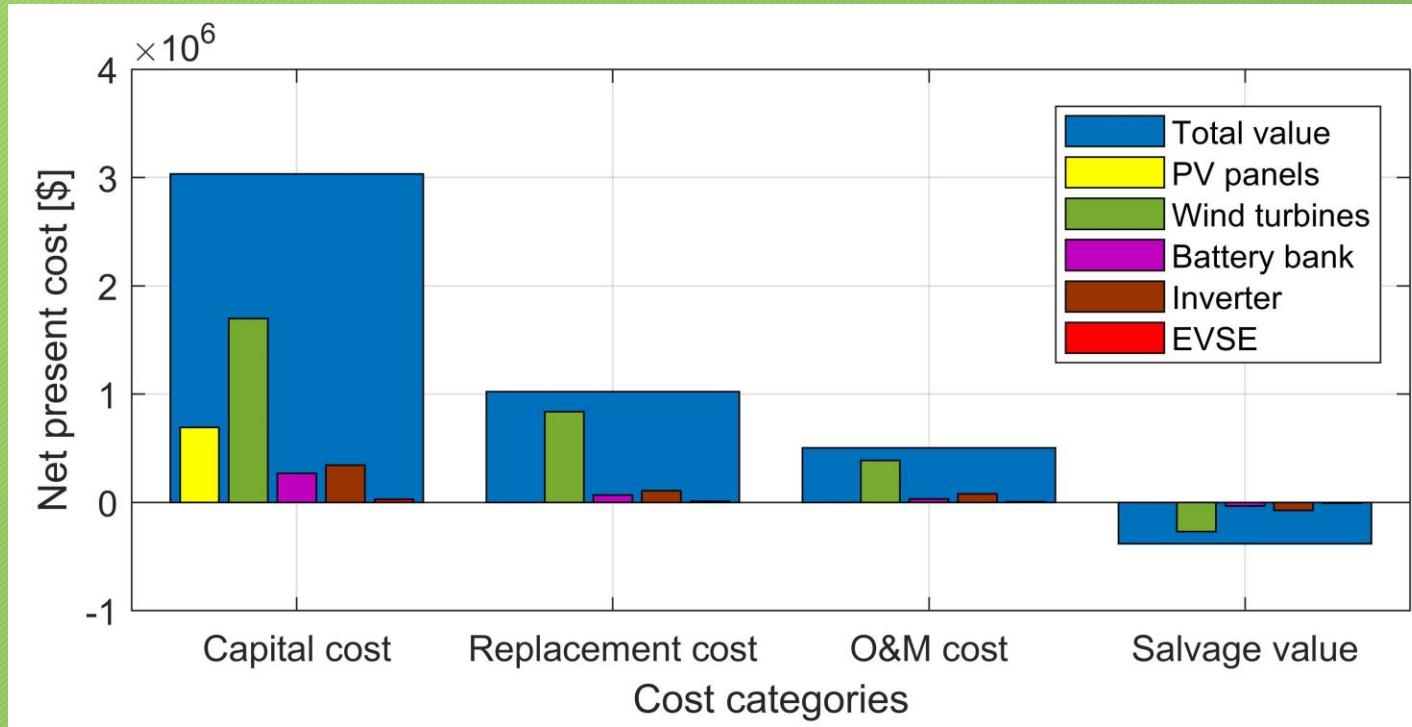


Fig. 9. Cash flow breakdown by components and cost categories

The NPC of the WT accounts for 61% of the TNPC

The capital cost of WT occupies about 65% of its NPC  dominant cost factor

LCOE=\$0.18/kWh < Actual (full) cost of electricity in Iran=\$0.21/kWh

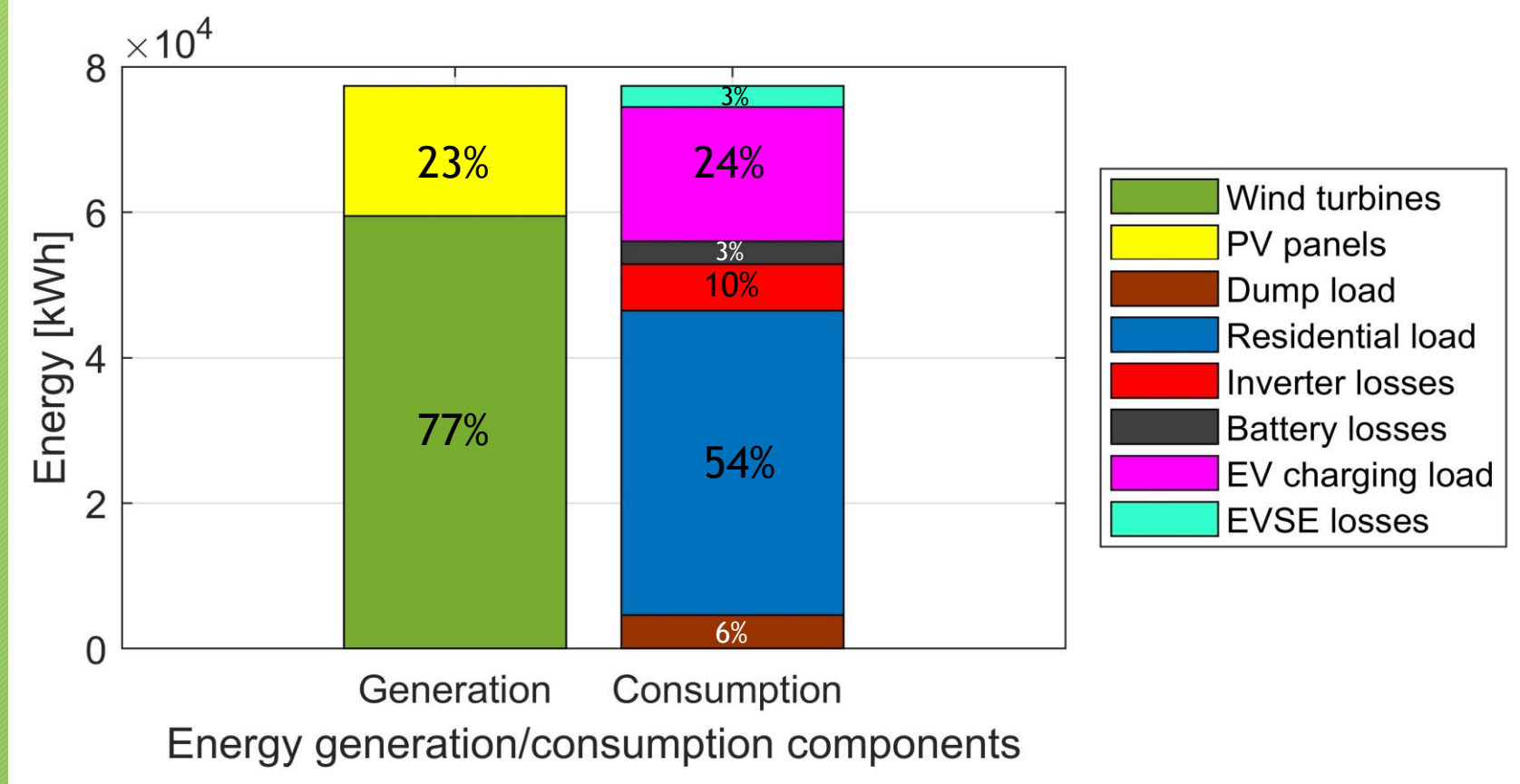


Fig. 10. Balance between the energy production and consumption

- The MFOA outperforms the most-preferred MHs used in this research area
- Data compression remarkably reduces the computational burden without sacrificing too much the solution accuracy
- DSM strategies have the potential to considerably decrease the micro-grid total cost
- To further our research, we intend to incorporate the uncertainties into the model using the MCS, enabled by the model reduction technique

- [1] S. Mirjalili, “Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm,” *Knowledge-Based Syst.*, vol. 89, pp. 228–249, 2015.
- [2] G. Mavrotas, K. Florios, and D. Vlachou, “Energy planning of a hospital using Mathematical Programming and Monte Carlo simulation for dealing with uncertainty in the economic parameters,” *Energy Convers. Manag.*, vol. 51, no. 4, pp. 722–731, 2010.
- [3] S. M. Hakimi, S. M. M. Tafreshi, and a. Kashefi, “Unit Sizing of a Stand-alone Hybrid Power System Using Particle Swarm Optimization (PSO),” *2007 IEEE Int. Conf. Autom. Logist.*, pp. 3107–3112, 2007.



Questions and Discussion