BIM-based Multi-Objective Building Life Cycle Energy Performance Evaluation Using Particle Swarm Optimization

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Abstract

Building energy performance evaluation is a multi-objective problem that plays crucial role in reducing environmental effects and energy costs, especially for energy importing countries to minimize its adverse effect on politics and economy. Moreover, two-fifth of world energy consumption and thirty percent of CO_2 emission belong to buildings and services. Building energy performance is estimated by steady state and dynamic energy calculation methods whereas dynamic simulation performs more accurate results than steady-state ones. However, despite being more effective, dynamic energy simulation tools such as EnergyPlus have limitations as they do not inherit parametric relationships between building elements even when design information is received from Building Information Modeling (BIM) tools. The parametric modeling features in BIM tools can be leveraged when building energy performance is calculated by using Dynamo visual programming interface to evaluate design alternatives.

In this study, a methodology to optimize building life cycle energy performance by exploring alternatives in material and geometric properties of building windows is explained. Multiobjective Particle Swarm Optimization (MOPSO), is used to minimize life cycle cost, life cycle CO_2 equivalent emission (GWP), and initial cost of building based on design alternatives altered via Dynamo-BIM interface. In this methodology, design alternatives are planned to be selected according to MOPSO coded in Dynamo based on energy performance of design variables measured by Green Building Studio and sent to Dynamo as outputs to calculate fitness values of objectives. In this study, Dynamo interacts with BIM software to change window properties and optimization algorithm is coded in Dynamo and tested with a multi-objective problem. The result shows that MOPSO works in Dynamo efficiently by generating multiple non-dominated solutions. As a future study, interaction between Dynamo optimization and Dynamo-BIM interface will be provided to optimize BIM-based building energy performance.

Keywords: Multi-objective optimization, BIM, energy analysis, Dynamo, Particle Swarm Optimization

1 Introduction

Energy is consumed continuously as it is required for all aspects of life quality, from the food embodied energy to energy used to produce and utilize the tools that ease human life to vehicles used for our transportation needs. Similarly, it is indispensable component of socio-economic development in the sectors of modern economies. The International Energy Agency (IEA 2014) statistics proves this idea that the comparison of energy production and consumption of different countries underline the fact that developed countries and energy exporting countries consume energy more than the others. In the last century, world energy consumption has risen significantly in an exponential trend which has caused significant depletion of non-renewable energy sources and increase of greenhouse gas releases that is expected to result in rise of global warming potential (GWP) with consequential significant changes in the life on Earth in the future (Rainforests.mongabay.com, 2015). Moreover, energy is a political card used time to time by energy exporting countries to manipulate the world politics and persuade other energy importing players with energy reduction threats to take their sides. Therefore, energy importers must develop energy strategies to minimize the adverse effect of their energy exports. The simple but efficient strategies are (i) to increase role of domestic energy resources by increasing share of renewable energy with improvement in renewable technologies and (ii) to maximize energy efficiency by developing energy efficient solutions to problems. Detailed energy analysis should be reported to see general perspective in energy demand and inefficiency in energy use. The world statistics indicates that three sectors such as building, transportation, and industry comprise major energy consumption in the world. The buildings consumes 40 % of world energy use and release 30% of total CO_2 emission (Shaikh et al 2014). The studies indicate that energy consumption in the building sector can be potentially saved up to 30 %, thanks to energy efficient buildings. In the residential buildings, building space heating and cooling account for nearly 70% of whole building energy consumption (Turkish Contractors Association 2014). Therefore, energy efficient strategies focusing on building heating/cooling needs could improve building performance significantly.

Decision making in the early design stage of the building life cycle impacts on the performance and cost-effectiveness of the buildings significantly (Aksamija 2012). Therefore, evaluation of design alternatives to improve building efficiency is expected to reduce life cycle costs and environmental impacts in considerable amounts (Stumpf et al 2009). The optimization of building performance in the design stage also eliminates possible troubles encountered in the retrofit projects such as taking insulation retrofit decision in multi-dwelling apartments that may take considerable time for approval of all residents and may have higher life cycle cost compared to ones added through early decision making (Laustsen 2008).

Accurate building energy use estimation in the early design stage plays crucial role in evaluating design alternatives in a correct manner. Performance of the buildings are forecasted according to calculation and measurement based energy estimation approaches. Measurement based energy estimation is generally preferred in retrofit projects because the performance of the building is measured during the building's operational stage and energy efficiency of all stakeholders are measured and strategies can be developed easily. On the other hand, in early design stage, energy use of the building is estimated by calculation based techniques due to scarcity of measured data. The simple calculation based energy estimation technique is using steady state energy calculation methods such as degree day method, bin method that eliminates details of interrelation between building components and their dynamic effects, and use of average temperature values for aggregated time intervals. It is easy and time efficient but less accurate method compared to dynamic methods where dynamic changes in the building energy loads and building system are directly reflected into energy models within hourly or sub-hourly weather data. Dynamic energy estimation is generally simulated by an energy simulation program directly such as EnergyPlus, eQUEST or a BIM-based simulation methodology is used where the building is modeled via BIM software and then exported into energy simulation program to run the simulation after adding some default data to the imported model. In the optimization procedure, similarly, the design alternatives in the energy model which is directly constructed or exported from BIM software are re-selected at each iteration to optimize the building performance. Parametric relations among building components, however, is not taken into consideration in the current energy models. The energy model must be re-constructed to adjust the changes in the models. In parametric modeling, on the other hand, the effects of the changes in any building component are updated automatically on other related building elements. Therefore, in BIM-based energy analysis, the model should be designed by different alternatives and exported to energy simulation tools to simulate performance of the building to get objective fitness value(s) of design alternatives. Then, the model should be updated in BIM software to leverage parametric intelligence and exported to simulation program again to get building performance results. BIM-based energy performance of the building is optimized according to procedure of the optimization algorithm using the simulation results as objective fitness values for that selected design alternative combination.

In this study, an optimization methodology to improve the performance of the buildings in their life cycle will be explained using a simple building that is modeled in a commonly used BIM software. The performance of the building life cycle is evaluated according to building life cycle cost, CO_2 equivalent emission (GWP), and initial cost. PE International 2012 and Ecoinvent 2012 databases via Gabi software are used to calculate GWP for each design alternatives. An efficient metaheuristic technique, Particle Swarm Optimizer (PSO) is used to optimize the multi-objective problem and find non-dominated Pareto optimal solutions. The rest of the paper is as follows. In Section 2, BIM-based energy analysis methods are explained. In Section 3, the basics of PSO is elucidated and implementation alternatives are evaluated. In Section 4, how the detailed energy optimization model is planned to be constructed is presented. Finally, the initial results are summarized and future work for improvement of the evaluation process is clarified in Section 5.

2 BIM-based Building Energy Performance and Optimization

BIM is data-enriched parametric representation of physical and functional characteristic of a facility that provides shared information for its life-cycle to be exchanged between the stakeholders. BIM can be used as communication and coordination tool to solve possible disputes encountered in construction process between stakeholders (Eastman et al 2008). Moreover, it may be possible to integrate and formulate different performance criteria of stakeholders, such as esthetics, structural reliability, energy performance, as a single multi-objective problem in order to solve them together to increase the value of the building model.

In majority of the buildings, efficient building performance design and analysis is ignored due to many reasons such as frequent changes in the building projects, insufficiency of mandatory energy codes that would increase energy awareness or lack of proper tools to model energy performance of the building accurately (Cho et al 2009). In traditional view, the building energy performance is analyzed just after necessary architectural and construction documents are already prepared to show that building energy design is suitable for the energy mandatory code(s) of the country. However, unanalyzed design alternatives cause opportunity loss to improve building performance in terms of performance criteria in its life cycle. The traditional CAD-based design and analysis tools lacks of integrated energy analysis. All stakeholders of the project design their parts according to their design performance criteria; however, the separate designing approach may cause conflicts between the designs due to lack of integration and communication/coordination between stakeholders. Moreover, traditionally in many work cultures, the contractors or project owners are inclined to minimize initial investment of the projects. Therefore, most of the time, minimization of initial investment cost of building project conflicts with minimizing life cycle cost of the building. As the awareness on life cycle approach increases, life cycle thinking spreads its effect on the building design. As BIM provides integration between designs of different stakeholders, it enables communication between all stakeholders in life cycle thinking approach and hence integrates the energy simulation tools with the building model promising to eliminate existing problems that are encountered in energy analysis.

In literature, BIM generally used to prepare energy model and exporting it into simulation tools as inputs such as eQUEST, EnergyPlus, IES/VE, TRNSYS (Oh et al 2011; Cormier et al 2011; Moon et al 2011, Chen & Gao 2011) . The missing information for the energy model is completed by default inputs of the simulation tools and the performance of the model is simulated by provision of interoperability between BIM and simulation program. In optimization problems, the transferred energy model is optimized by changing design variables according to optimization algorithm update procedure. In other approaches, limited number of design options is generated in BIM software and energy performance is estimated by simulation tool. Then, building energy performance fitness function is generated according to design variables and their objectives' values using regression analysis (Chen & Gao 2011). After that, performance of the building is optimized according to regressed energy fitness function using more alternatives. The approach used in this solution reduces run time of optimization algorithm, however decreases accuracy of building energy use estimation. Trade-off between accuracy of the model and run time is in the nature of the energy analysis. When the energy model is constructed in more detail, it provides more accurate results while waiting longer to get those results. In energy models where the design alternatives are updated in BIM software within its parametric rules, the energy model is constructed more accurately. Then, these alternatives are exported to simulation tool to get performance results and models are updated according to those results within optimization algorithm (Rahmani Asl et al 2013). Thus, this provides more flexibility to the resulting energy model and increases the accuracy of the model thanks to automatically parametric update of all components, which avoids possible errors in manual updates in BIM software and/or updates in simulation tools. Automation in BIM based energy modeling leads up studies on optimization of BIM-based building performance analysis. For instance, the BIM-based energy optimization study by Rahmani Asl et al (2014) demonstrates this approach where they optimize a residential building performance in a bi-objective problem using Non-dominated Sorting Genetic Algorithm-II(NSGA-II) to minimize energy use and maximize suitable daylighting level in the resident. They make use of visual programming that provides a graphical user interface to construct programming relationships without coding, to ease BIM information use for the analysis.

3 Multi-objective Optimization

Multi-objective optimization (MOO) models aim at evaluating the multiple and conflicting objectives of potential design solutions to provide suitable data for decision maker. In MOO, more than one solution alternatives are expected due to conflicting objectives except extreme cases where all objectives are optimized at one solution. The decision maker can evaluate alternative solution with respect to evaluation conditions that may change time to time and project to project. All alternative solution sets that cannot dominate other solutions at all objectives or can be dominated by others solutions are called non-dominated –Pareto optimal– solutions.

Multi-objective optimization problems can be formulated by different approaches such as weighted sum approach, ϵ-constraints method, goal programming and multi-level programming (Caramia & Dell'Olmo 2008). In weighted sum approach, all objectives are aggregated into a single objective function by giving weight factor for each objective function. Pareto optimal solution sets can be constructed by changing weight factors for objectives. In ϵ-constraints method, on the other hand, the optimization algorithm focuses on one of the objectives by constraining other objectives. According to given limits, the objective function is optimized whereas goal programming constrains all objectives and deviance from given constraints is tried to be minimized. In multi-level programming, objective functions are ordered in hierarchy. According to hierarchical order, all objectives are optimized one by one with respect to optimized objective constraints; however, in the last objectives, the result may become an infeasible solution due to the constraints.

In this study, a modified approach is constructed regarding the alternative approaches. All objectives are ordered according to its importance factor for decision maker and the most prominent one is called the main objective function. The optimization algorithm tries to optimize the main objective function while all non-dominated solution sets are used to generate new design sets to evaluate. Thus, the algorithm both focuses on the main objectives and try to explore all possible non-dominated solutions. The only weakness of the algorithm is that it may not find non-dominated solution sets that focuses on other objectives in detail; however, if the problem is available to construct the hierarchical order among objectives, it may not create a problem for the decision maker.

3.1 Particle Swarm Optimizer

Particle Swarm Optimization (PSO) is an efficient metaheuristic optimization algorithm which is used to find non-dominated solution sets to minimize life cycle cost, life cycle GWP and initial investment cost. PSO is a population based algorithm proposed by Kennedy & Eberhart (1995) by inspiring from social behavior of bird flocking, insect swarming and fish schooling. The algorithm is constructed on current condition of particle, its memory (its best solution up to now) and swarm memory (swarm global best solution up to now). The detailed step by step explanation of Particle Swarm Optimizer in multi-objective minimization problem, shortly called MOPSO, is as follows:

Step 1: All position and velocity vector of each particle is randomly initialized within given boundary limits for each design variable (Eq. 1-2). Set iteration t=0.

$$x_i^d(t) = X_{min}^d + r * \left(X_{max}^d - X_{min}^d\right) \; for \; d = 1,2,\dots,m \; and \; i = 1,2,\dots,N \qquad (1)$$
$$v_i^d(t) = X_{min}^d + r * \left(X_{max}^d - X_{min}^d\right) \qquad (2)$$

where $x_i^d(t)$ represents d[th] design variable of i[th] particle at iteration t within upper and lower boundary limits, X_{max}^d and X_{min}^d,. r and v is uniform random on interval (0,1) and velocity vector.

Step 2: Fitness functions for all objectives are evaluated for each particle.

Step 3: The memory of each particle is re-allocated by comparing its current fitness function with its best fitness up to now in its memory (Eq.3). If the particle is initialized (t=0), then, initial solution is assigned as local best positon into particle memory.
It updates the local best position for all individuals. If iteration is equal to 0, assigns position vector of individual as local best position.

$$p_i^l = \begin{cases} x_i(t) & f_1(x_i(t)) < f_1(p_i^l) \\ p_i^l & otherwise \end{cases} \qquad (3)$$

where, p_i^l is representation of i[th] particles' local best position.

Step 4: At t=0, the initial particle is assigned as best particle position. Then, objective fitness values of each particle are compared with the ones in best position vector. The solution set in best position vector is eliminated if the new generated solution dominates the particle objective fitness values. Moreover, the new generated solution is added into best positon vector if it cannot be dominated by solution sets in best position vector.

Step 5: Velocity and position vector of each particle are updated according to following formula:

$$v_i^d(t+1) = w * v_i^d(t) + c_1 r_1 * (p_i^{l,d} - x_i^d(t)) + c_2 r_2 * (p^{g,d} - x_i^d(t)) \qquad (4)$$
$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \qquad (5)$$

where, $p^{g,d}$ represents d[th] design variable of swarm best particle and w, c_1 and c_2 are inertia weight of individual to control exploration in the algorithm and constant trust parameters that may change to improve algorithm performance, respectively.
In velocity update, different local best solution for particle and swarm global best solution can be used to generate new design combination. In the first approach, non-dominated solution in both particle memory and swarm memory is kept and the solution set should be used in velocity update formula is selected randomly. In this approach, the optimization algorithm cannot be manipulated to minimize objective functions because the new solution is generated nearly randomly without manipulation. In second approach, local best position of the particles is updated according to main objective function and in velocity update, the single local best solution is used and one of the solution among global best position vector is randomly selected. Thus, the local best solution manipulates the algorithm to minimize main objective function and global best position manipulates the algorithm to scan more solution space to explore new solutions.

Step 6: Repeats steps 2-5 until termination criterion is met.

MOPSO is selected due to its property of fiting multi-objective optimization methodology that both concentrates on a main objective among multiple ones and generates non-dominated set of solution in wide solution space. In the next section, implementation of MOPSO on visual programming to optimize building energy performance will be explained in detail.

4 Methodology

In this study, a system approach that integrates visual programing with BIM is aimed to be developed to optimize building life cycle energy performance in multiple objectives in the early design stage of the building project to provide multiple non-dominated design alternatives for the designer in design decision making process. The building is planned to be modelled via BIM tool and the optimization model based on PSO algorithm is constructed in visual programming tool, Dynamo. Then, the two tools are planned to interact with each other using design alternative generation in Dynamo and parametric changes in building model and its energy simulation feature.

Dynamo is a visual programming tool that provides flexibility for users to both code via Python language in the tool and use built-in functions graphically without any coding which makes the tool easier to use and understand for non-programmers (Kron 2013). Dynamo interacts with BIM tool to change the properties of BIM elements automatically. This provides automated update in BIM tool to improve the performance of the building by constructing a BIM integrated optimization model in Dynamo.

In the integrated model, multiple Dynamo nodes are planned to be constructed using both built-in functions and Python coding to optimize multi-objective functions and talk with BIM tool to change building elements and run energy simulation. Up to now, the optimization part in the Dynamo interface, Multi-objective Particle Swarm Optimization (MOPSO), is constructed and changing building elements in BIM tool is provided in Dynamo. It is planned to integrate Dynamo and BIM elements and run energy simulation in GBS as part of our future study by basing our approach to the work of Rahmani Asl et al (2014). The details of planned BIM model and performance test of optimization model are explained in the next section.

In Dynamo interface, MOPSO is constructed as presented in Figure 1. The model starts with input parameters such as swarm size, constant PSO update parameters in Eq. 4 and boundary limits for each design variables. The initial design variables are created randomly in initialization custom node. The performance of each solution is evaluated by integrated design variables and fitness functions nodes. Fitness values of the main objective function (first fitness function) and initialized design variables for each particle are assigned as particle best fitness and particle best position. Then, all fitness functions of particles are compared with each other to create initial non-dominated solution sets. The model performance evolves in the main loop by giving all necessary constructed and initialized parameters used in Eq. 4 as inputs to generate new design variables and evaluate its performance with respect to others to construct Pareto optimal non-dominated solution sets while the termination criterion is met.

In the planned multi-objective optimization model, building life cycle cost, building life cycle GWP, and initial cost of the building will be evaluated to provide alternative non-dominated solutions for the decision maker. All necessary cost and GWP values for design alternatives will be given as input parameters via excel to Dynamo to calculate life cycle cost and life cycle GWP fitness values for design solution set. In complex models, instead of calculating the whole building cost and GWP in detail, comparative performance analysis can be used to both shortening the simulation time of the model as well as simplifying objective fitness functions by neglecting cost and GWP values of all constant building elements. In GWP performance of generated solution, all necessary GWP values for design alternatives are extracted from PE International 2012 and Eco-invent 2012 databases via Gabi software (Gabi 2013). Therefore, data existence in GaBi limits alternatives for each design variable. The initial cost of the

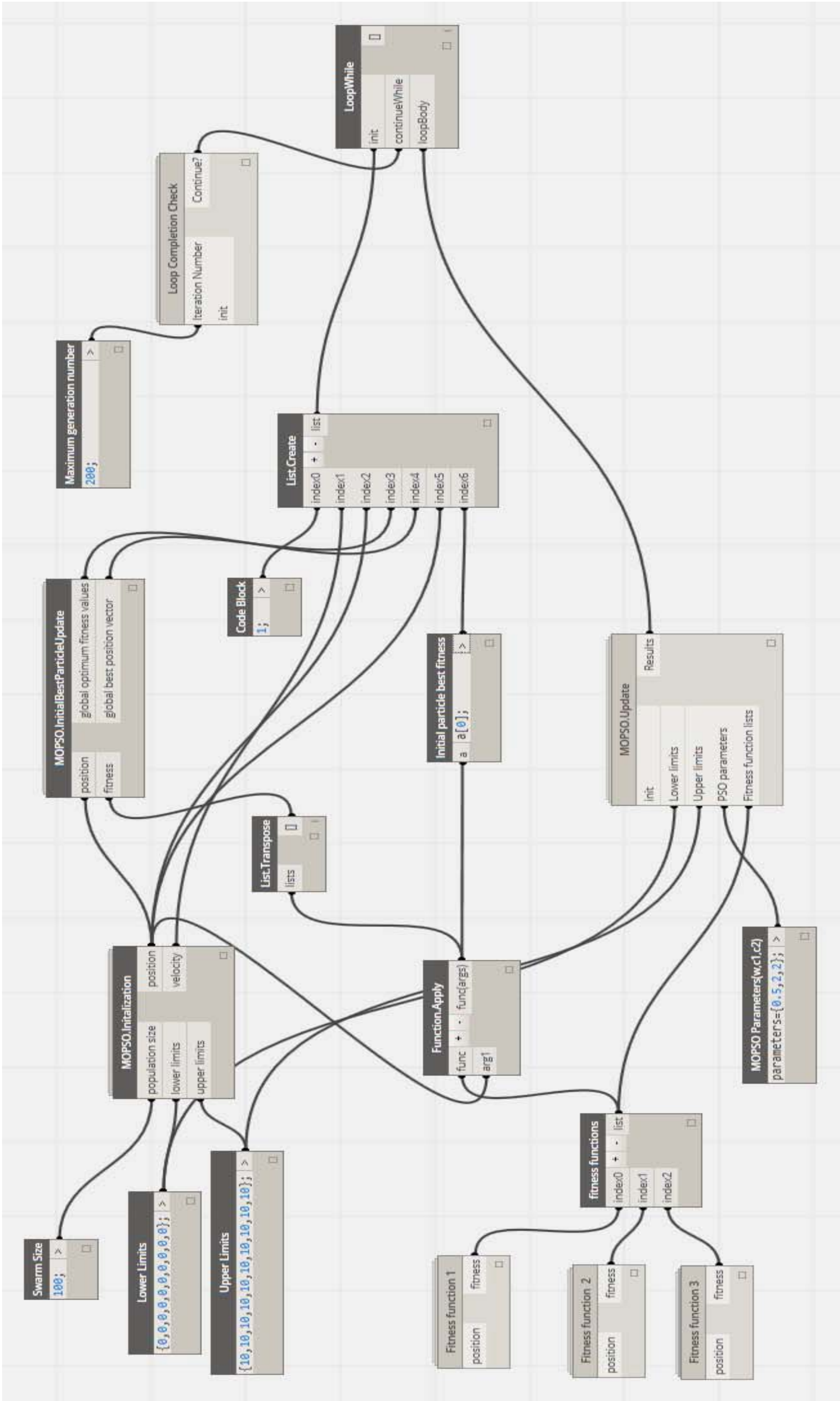

Figure 1. Multi-objective Optimization in Dynamo

buildings is calculated by summation of multiplication of building element amount by their costs, whereas life cycle cost and GWP are calculated by summation of initial cost/GWP and discounted building life cycle operational cost/GWP. Global warming potential of any design variable is directly extracted from GaBi database considering its amount from cradle to construction process. Operational GWP values of the building is obtained from GBS simulation result. Therefore, for each generated solution set, initial cost/GWP values combined with solution design and GBS simulation result are added to life cycle cost/GWP calculations to optimize Pareto-curve for the building model.

5 Case Study

A simple building is modelled in BIM tool to optimize building performance in multi-criteria to minimize building life cycle cost,GWP, and initial building cost that conflict with each other. Geometric and material information of the building elements are changed by the code in Dynamo to improve building life cycle energy performance.

The sample building is 50 m^2 rectangular shaped dwelling with multiple windows. In the integrated building, the geometrical properties of the windows such as height, width, family type (shape) and material property like glazing type is planned to be varied to find alternative solution sets with different window wall ratio to present Pareto-optimal solutions to decision maker/designer. A custom node code is developed to change building element properties in Dynamo. As seen in Figure 2, properties of the left window at the back face of the dwelling are re-designed by changing input parameters in the node (WindowSelection in Figure 2). The building model is planned to be reconstructed by changing input parameters for each window element in the model according to design variables coming from optimization algorithm. Then, the operational performance of the building will be evaluated by simulation runs in GBS and the results are planned to be used in the determination of life cycle cost/GWP fitness values. After that, the optimization model will try to find Pareto-optimal solutions by applying same procedure in the number of function evaluations which is equal to the multiplication of swarm size and maximum generation number.

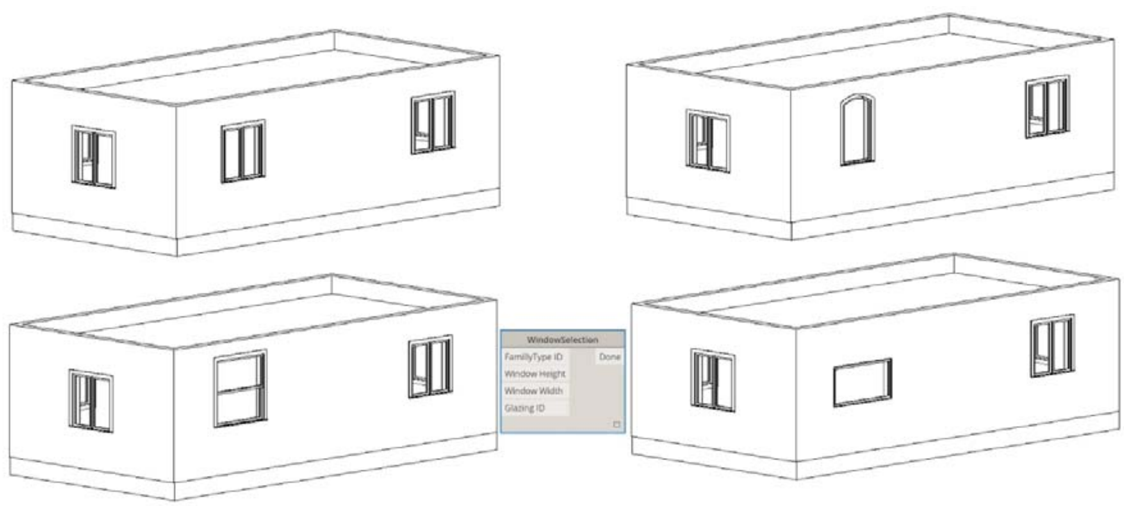

Figure 2. Window Property Change in Dynamo

The case study dwelling is planned to be optimized in the near future; however, the performance of the optimization code is needed to be tested to show its performance in Dynamo interface. A 10-dimensional unconstrained problem with three objectives is constructed for the optimization procedure. The details of the problem are as follows:

$$f_1(x) = \sum_{d=1}^{10} (x^d)^2 \quad (6)$$
$$f_2(x) = \sum_{d=1}^{10} (5 - x^d)^2$$
$$f_3(x) = \sum_{d=1}^{10} (10 - x^d)^2$$
$$0 < x^d < 10$$

In MOPSO implementation procedure, position update parameters w, c_1 and c_2 is selected as 0.5, 2, 2 respectively. Algorithm is implemented with 100 swarm particle by 200 generations, totally making 20.000 function evaluations. The algorithm runs in 33 seconds by generating 161 non-dominated solutions where the fitness results are graphed in Figure 3. The result shows that MOPSO in Dynamo can generate multiple non-dominated solutions efficiently.

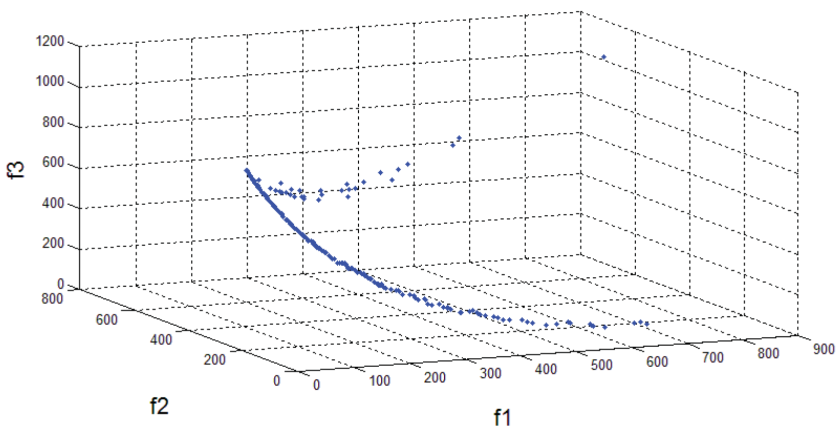

Figure 3. Fitness Graph of Non-dominated Solution Sets

6 Conclusion

In this study, a methodology to optimize BIM based building energy performance in terms of minimization of initial cost, life cycle cost, and life cycle GWP of buildings via visual programming, Dynamo, is explained. Optimization algorithm MOPSO is coded on Dynamo and performance of the algorithm is tested by 10-dimensional multi-objective problem. The results shows that MOPSO works in Dynamo efficiently by generating multiple non-dominated solution sets. Moreover, the interface between Dynamo and BIM model also works to update building element properties automatically. In further studies, it is planned to enable the interaction between BIM model and coded optimization algorithm on Dynamo interface, in order to optimize BIM-based building energy performance. This methodology can also be applied to retrofit projects. Thus, building life cycle energy performance optimization in both early design stage and retrofit projects could assist in reducing life cycle costs and potential GWP effects on the Earth.

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